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The emergence of specialization in heterogeneous artificial agent populations

Denton Cockburn
University of Windsor

THE EMERGENCE OF SPECIALIZATION IN HETEROGENEOUS ARTIFICIAL AGENT POPULATIONS

by

Denton Cockburn

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Declaration of Co-Authorship / Previous Publication

I. Co-Authorship Declaration

I hereby declare that this thesis incorporates the outcome of joint research undertaken under the supervision of Dr. Ziad Kobti. The collaboration is covered in Chapters 2, 3, 4 and 5 and 6 of the dissertation. In all cases, the key ideas, primary contributions, experimental designs, data analysis and interpretation, were performed by Denton Cockburn (the candidate) and Dr. Ziad Kobti (the supervisor) as primary authors and contributors. The work presented in chapter 6 contained significant data analysis performed by Stefani Crabtree from Washingston State University.

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Thesis Chapter	Publication title/full citation	Publication Status
2	The Effect of Social Influence on Agent Specialization in Small-World Social Networks CEC, 2009, 3172-3175	Published
3	Agent Specialization in Complex Social Swarms Studies in Computational Intelligence, vol. 248, 77-89	Published
4	WASPS: A weight-allocated social pressure system for the emergence of agent specialization ECAL, 2011, 161-167	Published
5	A Genetic and Social Hybrid Model for the Emergence of Agent Specialization	Unpublished
6	Simulating Social and Economic Specialization in Small-scale Agricultural Societies	Unpublished

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Abstract

In this dissertation, I present the Weight-Allocated Social Pressure System (WASPS). WASPS is a computational framework that when applied, can allow for the increase in agent specialization within a multi-agent population. Research has shown that specialization can lead to an overall increase in the productivity levels within a population [55]. WASPS aims to provide a mix of features from existing frameworks such as the genetic threshold and social inhibition models. It also subsumes these models, and allows hybrids of them to be created. It provides individual level behaviour as found in the genetic threshold model. As in some variations of the genetic threshold model [49], WASPS also allows for individual level learning. As found in the social inhibition models, WASPS allows for social influence, or population level learning. Unlike some models, WASPS allows agents to self-organize based on available tasks. In addition, it makes allowances for agents to allocate a resource among multiple tasks during a work period, wherein most models allow the selection of only one task.

WASPS allows the assumption that agents are heterogeneous in their task performance aptitudes. It thus aims to create skill-based agent specialization within the population. This will allow more skilled agents to allocate more resources to tasks for which they have comparative advantages over their competition. Because WASPS is self-organizing, it can handle the addition and removal of agents from social networks, as well as changes in the connections between agents. WASPS does not limit the definition of many or its parameters, which allows it to deal with changing definitions for those parameters. For example, WASPS can easily adjust to deal with changing definitions of agent skill and

influence. In fact, the individual level learning can be implemented in such a way that an agent can self-optimize even when it has no competitors to influence it.

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Chapter 1

Introduction

1.1 Background

1.1.1 Agent-Based Models

Agent-Based Modeling (ABM), also called Multi-Agent Systems, is a subfield of Distributed Artificial Intelligence. ABM is a computational model class that simulates the actions of and interactions between autonomous agents, with the aim of studying their overall impact upon the system. Unlike population based (top-down) models such as Genetic Algorithms, ABMs are individual based models whereby the operation of the system is the result of the collective actions of the agents (bottom-up). Agents are allowed to make decisions, learn, and interact with each other and their environment. Because system behaviour is a result of the actions of the individual agents, emergence is a central pillar of this area. Emergence is the appearance of complex system behaviour and patterns from relatively simple interactions, in this case between agents and their environment, as well as other agents. In ABM, population optimization is rarely a goal. This is due to the self-interested nature of the individual agents, whereby they may make decisions that may hurt others, but improve their own position. The field of ABM is expanding due to the increase in the level of computing power available. The complexity of an ABM is highly dependent upon the level of agent detail. As such, models can range from very simple to deeply involved and complex.

1.1.2 Village Ecodynamics Project

I am a student research member of the Village Eco-Dynamics Project (VEP) II team, which serves as the primary motivation for this work. VEP is a multi-disciplinary project with over 30 researchers in many different fields including anthropology, computer science, geology, economics, and ecology. The project is funded by the National Science Foundation in the United States (grant number 0816400). VEP includes an Agent-Based Model (ABM) that has been developed over the last 20 years. The ABM seeks to model the life of families living in the Four-Corners region of the US between AD 600 and AD 1300. The area was mostly depopulated at the end of this period and one of the primary goals of the research is to understand reasons that led to this depopulation [24, 52].

The original goal of the project was to understand why most Pueblo people would sometimes live in relatively compact villages, and at other times living primarily in dispersed hamlets. Research in the area such as tree-ring data used to produce specialized Palmer Drought Severity Indexes (PDSI) [51], which is a measure of meteorological drought, led to the examination of microeconomic processes at the level of the household in explaining whether settlement was dispersed or aggregated at any time.

The simulated model was initially designed by Tim Kohler [29] and a team of developers, Ziad Kobti and Robert G. Reynolds, from Wayne State University. The simulation relives the Indian settlements and farming practices based on collected data from sedimentation and other archaeological findings. The object of the model is to present an approach to understanding the behavior of the inhabitants and the reasons leading to their eventual disappearance from the region based upon modern archaeological knowledge of the region.

The study area has many ancient ruins and artifacts of the pre-Hispanic Pueblo Indians. Over the years much has been discovered in the study of this civilization. Initial research by Kohler tested environmental factors, concluding that these alone were not responsible for the depopulation of the region [29]. Kobti and Reynolds investigated the role of social interactions as a another possible explanation, using cultural algorithms and trading networks [26, 27].

The simulation creates agents, each representing a household, that live, work, and reproduce in a simulation based on the data collected on the region. Agents are responsible for gathering resources while feeding their families and trading with other agents. Agents can farm for maize, hunt for protein (which includes cottontail, jackrabbit, and mule deer), obtain water from rivers, springs, and other water sources, and also gather wood for the purposes of fuel from forests. The only recognized food source in the simulation is currently maize. While protein is required, it is not considered a form of calories to the agents. The model aims to accurately model soil productivity, rainfall, animal density, forest density, and other features of the region. Even the vegetation in the simulation that feeds the animals are affected by climate variability. Agents are responsible for providing their families with enough calories to perform these tasks, as well as basic metabolic needs. Agents keep track of family member households, resulting in different trade relationships between kin and non-kin agents. If an agent is not performing well at their present location, they will move to a more suitable location in the study area. Unfortunately for the agents, they are not allowed to exit the study area. When evaluating locations to move to, agents evaluate the resource productivity of that area. They evaluate the area for farming productivity, water accessibility and forestry presence.

One of the primary modes of interaction between agents in VEP is exchange. There are three different types of exchange enabled within the simulation, these are generalized reciprocal exchange, balanced reciprocal exchange, and barter exchange. Generalized reciprocal exchange allows trading between kin-related households. This network also allows the donation of excess goods to kin [44, 46, 54]. The balanced reciprocal exchange network (BRN) involves loan-based trade between unrelated agents within close proximity [28]. Agents are asked to repay these loans, increasing their reputation with the debtor if they do so, or damaging that reputation if they fail to repay. The barter network aims to allow trade between neighbours, regardless of relation, where an agent is short of one resource but may have excess amounts of another. Agents will trade with other agents within range that may have excess amounts of the resource they are seeking. This exchange network was introduced into the simulation in the work presented in 6. These exchange networks have so far demonstrated several items, such as increased agent populations, more resilient populations when there are short-term resource shortages (i.e. famine, drought), but more vulnerability during long-term shortages.

1.2 Motivation and *Desiderata*

In the current VEP II Agent-Based Model, agents perform only as much work as they assume they must to meet the needs of their family. On average, this is about 3 hours per day of work. Even by modern standards, this is an especially light work load. The unproductive situation lead to a question; if they were to perform more work what would they spend that extra time doing? Among the four tasks to be performed, how would agents decide to divide their time? This quesiton is backed up by anthropological evidence which has shown that agents spent more time on certain tasks than others, above and beyond what would be justified to simply meet their needs.

I therefore formalize the question as such:

Given agent Ag, the set of tasks available to Ag T_{Ag} and a resource R_{Ag}, how does an agent allocate its R_{Ag} among each task t in T_{Ag}? So, $\Sigma x_i = S(R_{Ag})$, where i is each task in T_{Ag}, $S(R_{Ag})$ refers to the amount of the resource R_{Ag} available, and x_i refers to a fraction of $S(R_{Ag})$. The problem also involves the following conditions: The problem is continuous over a period of iterations, $S(R_{Ag})$ changes between iterations and x_i is allowed to change over iterations.

1.3 Assumptions

I introduce WASPS (weight-allocated social pressure system), a self-organizing method for resource allocation among multiple tasks that takes into account the following factors:

- Agents are autonomous.
- Agents are connected via a social network.
- Agents have heterogeneous capabilities.
- Agents must allocate resource among multiple tasks.
- Agents are driven by social interactions and competition (population level learning).
- Agents also self-adjust (individual level learning).
- Social networks can be static or dynamic.

1.4 Objectives

I present a social, competition-driven self-organizing individual level framework for resource allocation among multiple tasks in Multi-Agent Systems, which:

- can be used to allow the emergence of population level dynamics such as task specialization;
- can subsume existing established frameworks such as the Genetic Threshold Model in the emergence of specialization;
- is a self-organized and sub-optimal resource allocation algorithm;
- can adjust to changes in the population of agents (such as addition and removal of agents);

- can adjust to changes in the size of social networks;
- can adjust to changes in the environment, such as changes in the definition of skill-level and influence rate;
- can allow for agent self-optimization in the absence of competition.

1.5 Contributions and Expected Benefits

WASPS is another computational model that leads to the emergence of agent specialization in multi-agent systems (MAS). In this respect, WASPS is not unique. What sets WASPS apart is its versatility and the additional problems it allows to be addressed. Unlike the primary existing models, WASPS allows skill-based emergence when agents possess different aptitudes for the tasks to be performed. It also allows for agents to divide a given resource among the available tasks, as opposed to committing all on one resource. It still allows for that as well, if required.

WASPS subsumes existing models such as the genetic threshold model and social inhibition model, with enough model flexibility to allow for the subsumation of other variations of those models. Because it uses both individual and population level learning, it makes it possible to create hybrid models involving both concepts. We expect WASPS to become one of the primary computational models for the emergence of agent specialization in MAS where there are multiple-factors that should drive that specialization. WASPS will also provide an interesting way to compare results across multiple models given the same environment.

While WASPS was undoubtedly motivated by the VEP, it is in no way limited to such an environment. The factors that WASPS addresses makes it applicable to many diverse domains, examples being biology, economics, computer science and sociology. Even then, we still would not limit it to these areas, and am sure there will be other applications that we do not yet foresee.

1.6 Dissertation Structure

The rest of the dissertation is structured as follows. In 2, we explore the idea of positive social influence leading to agent specialization. Agents possess a genetic threshold for available tasks. When the thresholds for multiple tasks has been surpassed, agents will consider the choices of their neighbours in choosing which task to perform. We focused on the study of this effect in small-world networks. Things such as human relationships [36] and even the connection of sites on the internet are small-work networks [9]. The probability of choosing a task would correlate with the number of neighbours performing that task. The more neighbours, the higher the probability. In this chapter, we discovered that this approach does lead to an increase in specialization when compared to the standard genetic threshold model. The effect was most prominent when there was an excess of task demand, due to more tasks being available for selection. We also noticed that the amount of influence exerted per neighbour made a difference.

In 3, we further explored this idea of what we have come to call the influence rate. Influence rate refers to the weight each agent has upon the task choices of its neighbours in a small-world social network. When neighbours had multiple choices available, they would consider the choices of their neighbours. The influence rate allowed for individual neighbours to have increased influence. The influence rate was compared at several different levels and with different levels of task demand within the environment. As the influence rate increased, so does the level of task specialization. This was found to be true in cases where agents shared the same constant influence rate, and cases where agents had varying influence rates. What we have found with further research is that the level to which this concept holds true is dependent upon the given context and domain. Given a system with a large number of tasks and a small level of agent connectivity, agents are much less likely to choose tasks not being performed by others. While this will result in a higher level of specialization, the counterpoint is that there will be a reduced level of diversity. More agents will be performing the same tasks. If a specialization has an effect on system resources, then this may result in one resource becoming depleted rapidly. This is in spite of the fact that agents will only perform specializations while demand exists.

In 4 we present a new social inhibition computational model for the emergence of specialization in agent societies. This computational model, called the Weight-Allocated Social Pressure System (WASPS) makes allowance for two big items; agents possess different skill levels for tasks, and agents can divide a resource among multiple tasks. This computational model is influenced by the behaviour of agents in biological systems such as wasp and ant colonies (hence the name). This model includes the idea of social influence, as well as individual level influence. Unlike the approach taken in the previous chapters though, WASPS makes use of social inhibition, or negative influence. Agents attempt to discourage neighbours from performing the same task. The computational model (we will also use the terms framework, method, and approach interchangeably with computational model throughout this dissertation) makes use of the influence rate, with the idea that it can be universal, or variable for each agent. The influence rate itself can then be based on some other factor (i.e. agent age), leading it to serve more as a function. Even the idea of individual level influence itself can be similar for all agents, or varied. This also can be used as a function that informs each agent how to change their allocations.

We showed that WASPS is able to significantly increase the level of specialization in a random population of heterogeneous agents. Agents can divide a resource (i.e. time) among available tasks. When agents possess different aptitude levels for tasks, competition and social pressure can lead to an increase in specialization. Agents will allocate more resources to tasks for which they have larger comparative advantages over their neighbours. Depending on the size of the networks, connectivity and number of tasks, we would notice that there would be very few agents that were fully specialized (allocating all resources to only one task). This would be because the agents would likely have advantages in multiple tasks. Also, because we used a weighted and normalized allocation scheme, some allocation changes may be offset by changes in other allocations.

WASPS was intentionally created with many abstract definitions. This makes the model more applicable to unforeseen domains. Many of the parameters were designed to allow for functions or constants. Agent interaction is also left open, allowing for broadcast, environmental exchange, message passing, or many other approaches. The social network, while we've tested with small-world, global and random networks, should still be applicable with other network arrangements. What the network refers to can be anything from a kin network, to a topographical neighbourhood, among other things.

In 5, we create a variation of the WASPS framework that includes the idea of a genetic threshold. The WASPS model presented in 4 is tested primarily as a social model. In this chapter though, we highlight the versatility of WASPS in handling individual level factors. The hybrid approach used in this chapter allows for agents to respond to levels of stimuli in the environment. While the general WASPS model doesn't specify how stimuli should be handled, this specific model shows one such way in which it can be incorporated. We saw that while this hybrid model led to an increase in the level of agent specialization, this level was lower than that seen in the pure genetic threshold model. On the other hand, the hybrid model did show increased skill-based specialization. It is our conclusion that there is a trade-off related to the hybrid model; a lower overall level of specialization, but a higher quality of work. This hybrid model allows for the study of specialization in populations of heterogeneous agents with different skills.

In 6, we implement the WASPS model within large multi-agent simulation environment. This is the Village Ecodynamics Project (VEP) which was introduced above. This served as a very big test for the WASPS framework. VEP includes many factors that would be important for the model to handle. For example, agents needed to maintain a certain level of resource storage. As such, this served as the primary factor for determining how agents could influence neighbours. The idea of neighbourhood was a topographical concept that was restricted to agents within a certain trading range. While agents would influence their neighbours into changing production, they would personally try to adjust their own production level to where they think it should be. This was already accounted for with the personal influence concept in WASPS. Put together, all this and other factors allowed WASPS to be used such that the agent population was able to emerge high levels of specialization. In the economic sense, this increased specialization had other effects on the market and population, which were further explored by my co-authors in that paper.

In 7 we present our conclusions, which summarize what the overall computational model can contribute. In addition, we also outline what we consider to be limitations to the usability of WASPS. Finally, we discuss areas that we would like to investigate further. We also consider the likelihood that there are potential uses and variations of WASPS that we are yet to think of, and may be things we cannot foresee.

Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants*. Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 – 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f37705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

Chapter 2

The effect of Social Influence on small-world social networks

2.1 Preface

In this unit we first begin to explore the topic of social influence in regards to specialization. We try a different approach than normally used in most of the literature; we use positive social influence. We consider positive social influence to be when an agent is driven to be like its neighbours. In this work, we did not draw any distinction between the level of influence of individual agents in comparison to others. Each agent had the same amount of influence on all of its neighbours.

We also involved the idea of demand levels. This would allow us to observe the behaviour of our approach given a shortage of demand (stimuli) for a task, a perfect level of demand, and an excess of demand. We were able to show that positive social influence was able to increase the level of task specialization within a population given all demand levels. This was a significant finding, as positive social influence was not used as a primary driver of agent specialization previously. Nonetheless, what we would consider the more important discovery in this work is the potential role of the level of influence upon the resulting level of specialization. We would later abandon the idea of positive social influence, but we thought to explore further the effect of what we would later call the influence rate upon the level of specialization.

2.2 Introduction

Specialization is the choice to produce one good or service, with reliance on others for other needed goods. The study of specialization is important to several fields. Archaeologists study specialization to understand the changes in societies as a result of the emergence of specialization. It also gives insight into why individuals would choose to produce certain goods over others. From the biological perspective, specialization helps to explain the behaviour of biological creatures such as ants, wasps and [32, 40, 42] and bees, which have been empirically shown to specialize based on tasks. Economically, specialization is studied to understand its effect upon a society's economy. It further serves to study how a market may grow or contract based on the specializations present, as these specializations lead to increases in the productivity of market systems [37]. Allyn Abbot Young points out that a productive individual increases the supply of certain commodities, while simultaneously increasing the demand for others [55]. This increase in productivity in turn increases per capita income according to Adam Smith [34]. Many of these fields use computer simulations to study the effect of specialization, so it's surprising that the simulation of specialization has not been studied more from a purely computer science perspective, with the exception of works such as [32].

There are several models that posit how specialization, also called division of labour, happens in groups. One common method is the genetic threshold model, explained more in the following section. This model is able to explain how caste systems evolve. We believe that there was also a social aspect to the idea of caste systems. For instance, we believe that having a lot of teachers in one's family will increase the likelihood of becoming a teacher. We believe that such a practice would increase the level of specialization in a system, which, as stated above, should lead to increased system productivity.

Many real-world social networks, such as the human acquaintance network, have been shown to be small-world networks, which are also explained below. We investigate the result of introducing social influence into small-world social networks, whereby an agent's choice of specialization is influenced by the choices of its neighbours. Given a choice between multiple specializations, we factor in what our neighbours are doing and allow that to influence our decision. We are limiting our study to autonomous agents, who make their decisions based on probabilities, as opposed to simply following a rule function. In addition, our agents' behaviours are also modeled after human agents, which fits into our research regarding the Pueblo people of the Mesa Verde region [28].

2.3 Genetic Threshold Model

While very little attention has been paid to the underlying genetic mechanisms for task specialization [53], several genetic models have been put forward for the study of specialization. The most widely used is the response threshold model. The threshold model presents a certain level of stimulus for each task at which an individual will choose to specialize in that task [49]. The threshold model has been backed up by empirical evidence in insect societies such as ants and bees [17, 40]. The response threshold model may in fact be an evolutionary behaviour, as agents that respond to problems (stimuli) quicker may be more likely to survive [23]. In the threshold model, agents by default perform no tasks. That is to say that if there is no stimulus for any of the possible tasks, then individuals will do nothing [5].

The determination of the level of stimulus present is dependent upon the context being studied. Even this has been approached from different angles, such as when all agents have the same stimulus levels for tasks, or when agents have differing thresholds based on individual genetic predispositions. In the latter case, low threshold individuals perform tasks at lower stimulus levels than others, and are thus more likely to specialize in those low stimulus tasks. The variance between individuals' threshold levels does not have to be significant, but seems necessary for the emergence of division of labour (DOL) in threshold models [23]. In some approaches, performing a task causes the threshold level for that task to decrease, while not performing the task will lead to the threshold level increasing [49]. Most threshold models assume these thresholds to be fixed throughout the individual's lifetime or simply as a result of having performed or rejected the task previously, but empirical evidence suggests that threshold levels change over time in natural systems [5, 42].

2.4 Small-world networks

A social network is a social structure made up of related items. These networks are graph structures where connecting edges represent a relation between the two items. For example, a family tree is a social network, where each edge represents that the two connected nodes are relatives. The small-world phenomenon demonstrates that all humans, and agents in similar networks, are linked via short paths of acquaintances. This phenomenon has been observed in many networks that were not designed to exhibit such features. This includes the famous "6-degrees of separation" feature found within the US population [36] and similar features found concerning the World-Wide Web [9]. Small-world networks [36] are social networks that exhibit this phenomenon.

There are multiple ways to create a small-world network. A small-world network can be created using the Barabási-Albert model [2], which creates a scale-free network. Scale-free networks are networks whose degree distribution follows a power law pattern. This pattern is very common in real-world networks, and is the cause of the '6-degrees of separation' feature. In these power law distributed networks, nodes are not evenly connected. In large networks, there are many well-connected hubs and many sparsely connected nodes. The general ratio between these hubs and others remains constant even as the network's size changes [3].

A small-world network can also be created randomly. In these networks, nodes will tend to have a small, average amount of connections. Thus, the likelihood of hub nodes would be very small. These random networks therefore end up being a poor reflection of real-world social networks.

2.5 Setup

Our testing methodology is very similar to [23]. Both papers aim to measure changes in the level of division of labor. We used the Repast Agent Simulation Model [39].

We use the genetic threshold model among our agents. For each simulation run, each agent is assigned a threshold for each task. The average threshold for each task is 50, which is the same as in [23] and arbitrarily chosen. Since research has shown that the amount of threshold level variation (as long as some exists) between agents is irrelevant [23], we chose to use only one level. Each agent therefore only deviated in the range of ± 5 from the average threshold for each task. The agent's threshold for each task would differ, but would remain the same for the duration of each simulation.

Most studies involve 2-5 possible specializations [53]. Some insect colonies have anywhere from 20 to 40 specializations [5], while in a human environment, such as New York City, there may really be thousands of possible job choices. [23] demonstrated that group size and task number play a role in the level of specialization within a system. We therefore tested using 2, 5, 10, 20, and 100 tasks. For group size, we used 2, 10, 20, 100, 500, 1000. That means that we had tests with 2 tasks and 2 individuals, tests with 2 tasks and 10 individuals, and so on. We felt that these numbers would provide a clear impression of specialization under varying parameters .

All agents initially select a task at the beginning of the simulation run, with none of them being inactive. At each iteration, an agent has a chance γ of switching specialization. γ is the same as used in [23], and arbitrarily chosen to be 0.2. If no task meets the agent's threshold then the agent becomes inactive. If an agent is inactive at the beginning of an iteration, it attempts to choose a specialization. First, the agent a filters all the possible tasks, creating a set F where F = $\{S > T_{\mathrm{at}}\}$, for all tasks t. It should be noted that the inactive state for agents is not considered a task. S_t is the amount of stimulus available for the task t. T_{at} refers to the agent's threshold level for task t. The agent then selects a task from F using the two methods being compared in this paper. In the standard genetic threshold model, an agent selects a random task from F. We propose selecting a task from

F that is influenced by the agent's network neighbours.

Given the set F, an agent selects one task, with a task t∈ F having probability: $\frac{1+\psi N_{at}}{\Sigma(\psi N_{aj})+\#F}$, for all tasks j in F, where N_{at} is the number of neighbours of agent a that are currently engaged in task t, and #F represents the total number of tasks in F. We use the symbol ψ to represent the influence impact an agent has on its neighbours selection. We arbitrarily set this at 0.5 x #F, as preliminary tests showed no pattern from increasing or decreasing this value. We intend to explore that idea in future research. When selecting tasks that neighbours are engaged in, we ignore those neighbours that are currently inactive.

Our simulation also included the concept of demand. Demand is the total amount of effort needed to satisfy all tasks relative to the total work ability of all agents. A demand level $\delta < 1$ indicates that there is less work available than can be performed by all agents, thus potentially leading to inactive agents. We tested with demand levels of 0.7, 1, and 1.3.

At the beginning of each iteration, including the first, the stimulus level for each task is updated. The stimulus update formula is the same as used in [23]. Each agent performs the amount of work, a, which is arbitrarily assigned as 3. Each task Tj is updated by Bj = $a\frac{N}{T}\delta$, where N is the number of agents, T is the number of tasks, and δ is the previously mentioned demand level. This means that the stimulus level for a task is reduced when an agent performs that task. Therefore it is possible to exhaust the demand for each task, especially when the demand level δ is below 1.

At the beginning of each simulation, we create a social network using the Barabási-Albert [2] model. This model creates a small-world network, wherein all agents are connected to all other agents, but not necessarily directly. The connnections between agents are fixed for the duration of each experiment. To compare the performance of the two strategies, we ensure that the created network is the same for both strategies. This does not mean that we use the same social network for every simulation. Each social network is used twice for each combination of parameters, once for the strategy using random selection model, and once using our social influence selection model, which is what we compare. In addition, each combination of parameters was tested with 10 different initial social networks, for a total of 1200 comparisons.

We use a method developed by Gorelick et al. to measure and compare our results. The method calculates and quantifies the degree to which agents are specialized [19]. It requires that the chosen specialization of all agents is recorded. We do this by having each active agent record its specialization at the end of each iteration. The recorded information of all agents is then stored in a nxm matrix, where n indicates each agent and m each task. The matrix is then normalized such that the sum of all cells is 1. The method developed in [19] then calculates the mutual information and Shannon entropy index [47]for the distribution of individuals across tasks. The result of dividing that mutual information score by the shannon entropy score indicates how specialized agents were, with a result between 0 and 1. A score of 1 indicates that all agents are fully specialized, while 0 indicates no specialization. This is the same method used in [23]. More details of the methodology can be found in [19].

2.6 Results and Discussion

For easy comparison of the levels of specialization, we normalize the results of each strategy by dividing the resulting of social influence by that of the genetic threshold model. Therefore, a division of labour (DOL) ratio of 1.1 would indicate that there was 10% more average specialization under social influence than under the genetic threshold model. Our results across the varying set of parameters are presented in Tables 1-4.

Table 2.1: DOL ratios at 0.7 demand level. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model.

	2	10	50	100	500	1000
2	0	1.12	1.17	1.11	1.12	1.1
5	1.12	0.99	1	1.05	1.05	1.05
10	0.96	0.97	0.99	1.02	1.01	1.01
20	0.76	0.88	1.01	0.99	1	1
100	0.92	1.01	1	1	1	1

Table 2.2: DOL ratios at 0.9 demand level. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model.

	2	10	50	100	500	1000
2	0	1.65	1.21	1.18	1.16	1.16
5	2.19	1	1.04	1.04	1.14	1.14
10	0.63	0.98	1.04	1.04	1.06	1.07
20	0.52	0.95	1	0.99	1.01	1.02
100	0.83	0.98	0.97	0.99	1	1

Table 2.3: DOL ratios at a demand level of 1. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model.

	2	10	50	100	500	1000
2	0	1.09	1.34	1.32	1.2	1.23
5	1.9	1.08	1.03	1.11	1.2	1.2
10	0.65	0.99	1.1	1	1.18	1.17
20	0.54	1.02	1.06	0.83	1.09	1.1
100	0.77	1	1.04	0.86	1	1

Table 2.4: DOL ratios at 1.3 demand level. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model.

	2	10	50	100	500	1000
2	0	1.33	1.08	1.13	1.17	1.26
5	1.64	1.11	1.16	1.17	1.22	1.22
10	0.55	1.17	1.18	1.19	1.24	1.23
20	0.65	1.03	1.18	1.18	1.23	1.23
100	0.77	0.99	1.08	1.1	1.17	1.18

Three patterns seem to emerge given Tables I-IV. First is that social influence increases the level of specialization, shown by cell numbers greater than 1. Even when demand level is lowest at 0.7, when social influence is expected to be lowest, there is still a general increase of specialization. The second is that the effect of social influence also increases as the number of agents increase. Finally, we notice that the effect also increases as the demand level increase. Note the general growth of the ratio as we move from a demand level of 0.7 through to a demand level of 1.3. This is in spite of the fact that division of labour is known to drop significantly (almost nil) as demand levels exceed 1. We set the value of the cell at 1x1 to 0, as the level of specialization was so low that it rendered any meaningful comparison meaningless.

When demand level is below 1, agents have fewer specializations that will have enough stimulus to surpass their thresholds. As lower stimulus lead to more inactive agents, the chance of these agents suddenly coming upon multiple tasks that were under-worked is slim. We expected litle to no increase from social influence here. This is due to the fact that social influence only plays a role when an agent has multiple specializations from which to choose. The results indicate that even when there is low demand, enough agents are still faced with multiple choices, resulting in an specialization from social influence.

When the demand level is 1, the amount of stimulus added is exactly equal to the amount of work able to be performed. Excess stimulus only remains when agents are not properly tasked - either because they are inactive, or on a task which doesn't have enough work for them to perform. There will be a few agents that are misplaced (inactive or under-productive), resulting in a slight increase in the level of excess stimulus per iteration. This situation will lead to more agents having multiple tasks above their threshold level. This causes a further increase in specialization than that seen at the lower levels.

A demand level above 1 indicates that even if all agents are active and fully worked, they are not able to satisfy all the stimulus in the system. As the level of excess stimulus increases per iteration, agents will have more tasks available that surpass its threshold. When an agent's neighbourhood remains consistent - where its neighbours are maintaining their specialization, there is a higher probability of it choosing the more popular tasks, as determined by its neighbours. We found that while specialization was very low when demand level was above 1, there was still an increase from social influence.

Because the choice that an agent makes is based on a probability, there still remains a chance that an agent will choose a specialization that none of its neighbours have chosen. As this will in turn influence those neighbours decisions, its possible that in a few cases social influence may actually decrease specialization over a short period of time. This is especially pronounced in small networks, as the effect of choosing new specializations will cascade more quickly, having a greater effect on the entire network. We believe this to be the explanation for the cases in our experiments where there is a reduced level of specialization where an increase is expected.

We also noticed that agents striving to "follow the Joneses" when choosing specializations also result in a sort of topology based caste system. In cases where demand level is significantly above 1, agents will tend more to choose the same specializations as their neighbours. This has a cascading effect, as one agent changing its specialization will influence its neighbours to also follow suit. In the extreme case where tasks have more stimulus than can be performed by all agents, the result will be that all agents may converge upon performing one task. Even when all agents have converged, there is still a chance that an agent may choose a specialization not performed by any of its neighbours, even if all agents are directly connected. We can deduce that the likelihood of convergence is also dependent upon the connectivity of the social network. The more neighbours an agent has, the more influence exerted upon its decisions.

2.7 Conclusion and future work

In this paper we examined the effects of a social influence strategy on an agent's choice of specialization. We found that social influence increases division of labour when there is an excess of demand. When influenced by their peers, agents become more specialized when there is too much task choice available. Our results reinforce the findings of previous research that indicate that specialization increases as group size and task number increases, which is also found in human societies [7]. Our research further shows that in such settings, social influence increases the level of specialization above and beyond the increase from those factors.

In the future, we'd like to examine other social strategies for division of labour, perhaps with the goal of comparing these to find the most effective. One such idea is to investigate the desire of agents to find niches. We are interested in studying what effect the drive to be different has on division of labour. This was addressed in [53], where agents chose their specialization based on the result of a function that weighs both their threshold levels and inverse social influence. We believe that there is more room for investigation with regards to that approach. In keeping with that view, we'd like to compare these different approaches, perhaps even hibridizing them, to understand the effect.

Another idea we would like to investigate is the effect of social influence on stimulus perception. In this paper, we studied in this paper the effect of social influence after a task has already surpassed the agent's threshold. We would like to study the idea that if more of our neighbours are performing a task, it becomes "cooler". The underlying idea being that such an effect may reduce an agent's innate threshold for that task, allowing them to perform tasks which they may not have if they were not influenced.

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Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants*. Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 – 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f3705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

Chapter 3

Agent Specialization in Complex Social Swarms

3.1 Preface

This unit builds directly upon the previous unit. In this unit though, we wanted to further explore how much of an effect the influence rate has upon the level of specialization. We used the symbol ψ to refer to the influence rate, a notation which was not used in subsequent work. We tested the effect under several scenarios, many carried over from the previous unit. The first test idea is using universal influence rates (every agent has the same influence upon its neighbours). What we noticed given that situation was that the level of specialization would tend to increase along with ψ, petering out around $\psi = 0.8$. The idea of trying to find a stable point was influenced by the method used in Ant Colony Optimization, where the parameter determining the level of pheromone strength was settled on by trial and error, with there being no agreement on what the "best" value is [15].

Following our tests with universal influence rates, we tried variable rates for agents, but within a certain average. Again we observed that the level of specialization would increase as ψ increased, and again we noticed the result becoming rather stable at around

$\psi = 0.8$. This work was not able to demonstrate what we hoped for, which was a stable point for which ψ would produce optimal results. While the result would slow down at $\psi = 0.8$, it would still seem to increase slightly while going higher, showing that point to be suboptimal. In spite of this failure, we were still able to see that the influence rate had significant effects upon the level of task specialization within the population. Due to the failure to prove some optimal level for ψ, we were lead to move away from positive social influence as a difinitive method for the emergence of agent specialization in populations. We would still make use of ψ though.

3.2 Introduction

Agents are typically autonomous objects able to reason about their environment to maximize individual goals. Agent populations with communication and sophisticated social structure, likes that observed in ants, often yields to limitations in maximizing individual goal and instead settle for a goal appeasing to the population. An effect of socialization is specialization, that can be described as a subset of choices that an agent selects or frequents more than others. Social exchange and the distribution of specializations makes up for the lost individual productivity and increases reliance on the social network.

The study of specialization is important to several fields. Social scientists and biologists for instance study specialization to better understand the changes in societies as a result of the emergence of specialization. It also gives insight into why individuals would choose to produce certain goods over others. From the biological perspective, specialization helps explain the behaviour of biological creatures such as ants, wasps and bees[32, 40, 42], which have been empirically shown to specialize based on tasks. Economically, specialization is studied to understand its effect upon a society's economy. It further serves to study how a market may grow or contract based on the specializations present, as these specializations lead to increases in the productivity of market systems [37]. Allyn Abbot Young points out that a productive individual increases the supply of certain commodities, while simultaneously increasing the demand for others [55]. This increase in productivity in turn increases per capita income according to Adam Smith [34]. Many of these fields use computer simulations to study the effect of specialization, so it is surprising that the simulation of specialization has not been studied more from a purely computer science perspective, with the exception of works such as [32].

There are several models that posit how specialization, also called division of labour, happens in groups. One common method is the genetic threshold model, which states that agents possess an inherent threshold for task stimulus, and when that threshold is exceeded, the agent will perform that task. This model is able to explain how caste systems evolve. We believe that there was also a social aspect to the idea of caste systems. For instance, we believe that having a lot of teachers in one's family will increase the likelihood of becoming a teacher. We hypothesize that such a practice would increase the level of specialization in a system, which in turn should lead to increased system productivity.

There is also a social aspect to division of labour, such as the activator/inhibitor studies [5, 43]. These show that in certain insect colonies such as bees, certain bees evoke pheromones that suppress the desire of other agents to want to perform a task. Agents' desire to perform certain tasks would change as they age. This activator/inhibitor action would result in highly specialized colonies along the lines of age, in an effect called age polyethism. The idea of social influence is that an agent's choice of which task to specialize in when multiple ones are available, is influenced by the choices of its neighbours. Using a metric that measures the level of specialization within a system [19], we find that social influence leads to an increase in division of labour.

Social networks are an integral component of social systems. In this study we limit our networks to those exhibiting small-world properties, as these have been shown to resemble real world networks [3]. Some real-world networks that have been found to be small-world networks are the human acquaintance network and the world wide web. [9, 36]. Keeping the focus on human agent specialization, we assume in this study that agents are autonomous, among other things, they are able to make their decisions based on probabilities, as opposed to simply following a rule function.

Many real-world social networks, such as the human acquaintance network, have been shown to be small-world networks, which are also explained below. We investigate the result of introducing social influence into small-world social networks, whereby an agent's choice of specialization is influenced by the choices of its neighbours. Given a choice between multiple specializations, we factor in what our neighbours are doing and allow that to influence our decision. We are limiting our study to autonomous agents, who make their decisions based on probabilities, as opposed to simply following a rule function. In addition, our agents' behaviours are also modeled after human agents, which fits into our research regarding the Pueblo people of the Mesa Verde region [28].

The object of this paper is to examine the effects of social influence on autonomous yet social swarms. Particularly sensitize the ranges of influence parameters on the degree of specialization emerging in such populations. In section 2 we describe the genetic threshold model and underlying generic mechanisms for task specialization. In section 3 we briefly introduce an overview of relevant definitions and concepts on small-world networks. Section 4 outlines the approach taken to model social influence. Experimental work and results are discussed in section 5. Finally, we conclude and summarize our finding with some highlights of potential future ventures.

3.3 Genetic Threshold Model

A number of variables contribute to the overall makeup of social influence and specialization in general. Included are genetic threshold level, economic demand level, and social influence rate. While very little attention has been paid to the underlying genetic mechanisms for task specialization [53], several genetic models have been put forward for the study of specialization. The most widely used is the response threshold model. The threshold model presents a certain level of stimulus for each task at which an individual will choose to specialize in that task [49]. The threshold model has been backed up by empirical evidence in insect societies such as ants and bees [17, 40]. The response threshold model may in fact be an evolutionary behaviour, as agents that respond to problems (stimuli) quicker may be more likely to survive [23]. In the threshold model, agents by default perform no tasks. That is to say that if there is no stimulus for any of the possible tasks, then individuals will do nothing [5].

The determination of the level of stimulus present is dependent upon the context being studied. Even this has been approached from different angles, such as when all agents have the same stimulus levels for tasks, or when agents have differing thresholds based on individual genetic predispositions. In the latter case, low threshold individuals perform tasks at lower stimulus levels than others, and are thus more likely to specialize in those low stimulus tasks. The variance between individuals' threshold levels does not have to be significant, but seems necessary for the emergence of division of labour (DOL) in threshold models [23]. In some approaches, performing a task causes the threshold level for that task to decrease, while not performing the task will lead to the threshold level increasing [49]. Most threshold models assume these thresholds to be fixed throughout the individual's lifetime or simply as a result of having performed or rejected the task previously, but empirical evidence suggests that threshold levels change over time in natural systems [5, 42].

3.4 Small-world networks

A social network is a social structure made up of related items. These networks are graph structures where connecting edges represent a relation between the two items. For example, a family tree is a social network, where each edge represents that the two connected nodes are relatives. The small-world phenomenon demonstrates that all humans, and agents in similar networks, are linked via short paths of acquaintances. This phenomenon has been observed in many networks that were not designed to exhibit such features. This includes the famous "6-degrees of separation" feature found within the US population [36] and similar features found concerning the World-Wide Web [9]. Small-world networks [36] are social networks that exhibit this phenomenon.

There are multiple ways to create a small-world network. A small-world network can be created using the Barabási-Albert model [2], which creates a scale-free network. Scale-free networks are networks whose degree distribution follows a power law pattern. This pattern is very common in real-world networks, and is the cause of the '6-degrees of separation' feature. In these power law distributed networks, nodes are not evenly connected. In large networks, there are many well-connected hubs and many sparsely connected nodes. The general ratio between these hubs and others remains constant even as the network's size changes [3].

A small-world network can also be created randomly. In these networks, nodes will tend to have a small, average amount of connections. Thus, the likelihood of hub nodes would be very small. These random networks therefore end up being a poor reflection of real-world social networks.

3.5 Approach using Social Influence

Social influence is the concept that an agent's choice of specialization is influenced by the choices of those within its social network. Given a choice between multiple specializations, we factor in what the agent's neighbours are doing and allow that to influence the agent's decision. An agent N is defined as a neighbour of an agent A if N and A are directly connected within the social network. It has been shown that in the majority of cases, social influence causes an increase in the level of agent specialization when compared to systems with no social influence.

Waibel and his team in [53] also used the concept of social influence, but with what essentially were fully-connected networks (where all agents are connected to all others). In that study, agents chose their specialization based on the result of a function that weighs both their genetic threshold levels and inverse social influence. Therefore, chance of an agent choosing a task would reduce when more agents are already performing that task. This is similar to the activator/inhibitor model, but without the age factor implied in that model.

Our testing methodology is very similar to [23]. Both papers aim to measure changes in the level of division of labor. We used the Repast Agent Simulation Model [39].

We use the genetic threshold model among our agents. For each simulation run, each agent is assigned a threshold for each task. The average threshold for each task is 50, which is the same as in [23] and arbitrarily chosen. Since research has shown that the amount of threshold level variation (as long as some exists) between agents is irrelevant [23], we chose to use only one level. Each agent therefore only deviated in the range of ± 5 from the average threshold for each task. The agent's threshold for each task would differ, but would remain the same for the duration of each simulation.

Most studies involve 2-5 possible specializations [53]. Some insect colonies have anywhere from 20 to 40 specializations [5], while in a human environment, such as New York City, there may really be thousands of possible job choices. [23] demonstrated that group size and task number play a role in the level of specialization within a system. We therefore tested using 2, 5, 10, 20, and 100 tasks. For group size, we used 2, 10, 20, 100, 500, 1000. That means that we had tests with 2 tasks and 2 individuals, tests with 2 tasks and 10 individuals, and so on. We felt that these numbers would provide a clear impression of specialization under varying parameters.

All agents initially select a task at the beginning of the simulation run, with none of them being inactive. At each iteration, an agent has a chance γ of switching specialization. γ is the same as used in [23], and arbitrarily chosen to be 0.2. If no task meets the agent's threshold then the agent becomes inactive. If an agent is inactive at the beginning of an iteration, it attempts to choose a specialization. First, the agent a filters all the possible tasks, creating a set F where F = $\{S > T_{\mathrm{at}}\}$, for all tasks t. It should be noted that the inactive state for agents is not considered a task. S_t is the amount of stimulus available for the task t. T_{at} refers to the agent's threshold level for task t. The agent then selects a task from F using the two methods being compared in this paper. In the standard genetic threshold model, an agent selects a random task from F. We propose selecting a task from F that is influenced by the agent's network neighbours.

Given the set F, an agent selects one task, with a task t$\in$ F having probability: $\frac{1+\psi N_{\mathrm{at}}}{\Sigma(\psi N_{\mathrm{aj}})+\#F}$, for all tasks j in F, where N_{at} is the number of neighbours of agent a that are currently engaged in task t, and #F represents the total number of tasks in F. We use the symbol ψ to represent the influence impact an agent has on its neighbours selection. We will examine the sensitivity of the specialization level to changes in ψ by comparing results using varying levels. We use $\psi = 0.5$ as a baseline by which we compare other results. When selecting tasks that neighbours are engaged in, we ignore those neighbours that are currently inactive.

We tested with constant levels of ψ for all agents at 0, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1. Note that when ψ is constant, all agents share the same influence rate. We also tested ψ with rates that vary between agents. For each level, we created a normal distribution with a set mean. These levels were 0.2±0.1, 0.3±0.1, 0.4±0.1, 0.5±0.1, 0.6±0.1, 0.7±0.1, 0.8±0.1, 0.9±0.1, 1±0.1, and 0.5±0.5.

The simulations also included the concept of demand. Demand is the total amount of effort needed to satisfy all tasks relative to the total work ability of all agents. A demand level $\delta < 1$ indicates that there is less work available than can be performed by all agents, thus potentially leading to inactive agents. We tested with demand levels of 0.7, 1, and 1.3.

At the beginning of each iteration, including the first, the stimulus level for each task is updated. The stimulus update formula is the same as used in [23]. Each agent performs the amount of work, a, which is arbitrarily assigned as 3. Each task Tj is updated by Bj = $a\frac{N}{T}\delta$, where N is the number of agents, T is the number of tasks, and δ is the previously mentioned demand level. This means that the stimulus level for a task is reduced when an agent performs that task. Therefore it is possible to exhaust the demand for each task, especially when the demand level δ is below 1.

At the beginning of each simulation, we create a social network using the Barabási-Albert [2] model. This model creates a small-world network, wherein all agents are connected to all other agents, but not necessarily directly. The connections between agents are fixed for the duration of each experiment. To compare the performance of the two strategies, we ensure that the created network is the same for both strategies. This does not mean that we use the same social network for every simulation. Each social network is used twice for each combination of parameters, once for the strategy using random selection model, and once using our social influence selection model, which is what we compare. In addition, each combination of parameters was tested with 10 different initial social networks, for a total of 1200 comparisons.

We use a method developed by Gorelick et al. to measure and compare our results. The method calculates and quantifies the degree to which agents are specialized [19]. It requires that the chosen specialization of all agents is recorded. We do this by having each active agent record its specialization at the end of each iteration. The recorded information of all agents is then stored in a nxm matrix, where n indicates each agent and m each task. The matrix is then normalized such that the sum of all cells is 1. The method developed in [19] then calculates the mutual information and Shannon entropy index [47]for the distribution of individuals across tasks. The result of dividing that mutual information score by the Shannon entropy score indicates how specialized agents were, with a result between 0 and 1. A score of 1 indicates that all agents are fully specialized, while 0 indicates no specialization. This is the same method used in [23]. More details of the methodology can be found in [19].

3.6 Results and Discussion

For uniform comparison of the levels of specialization, we first establish certain boundary tests by comparing levels of ($\psi = 0.5$) and ($\psi = 1 \pm 0.1$) to the standard genetic threshold model ($\psi = 0$) across varying parameters. Once we've established this, we proceed to use ($\psi = 0.5$) as our baseline to study the results at other levels. We normalize the results of each strategy by dividing the resulting of social influence by a baseline of ($\psi = 0$) in Tables 1-8 and ($\psi = 0.5$) in Tables 9-12. Therefore, a division of labour (DOL) ratio of 1.1 would indicate that there was 10% more average specialization than in the respective baseline model.

3.6.1 Comparison to genetic threshold model ($\psi = 0$)

Table 3.1: DOL ratios at 0.7 demand level, with $\psi = 0.5$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	0	1.12	1.17	1.11	1.12	1.1
5	1.12	0.99	1	1.05	1.05	1.05
10	0.96	0.97	0.99	1.02	1.01	1.01
20	0.76	0.88	1.01	0.99	1	1
100	0.92	1.01	1	1	1	1

Table 3.2: DOL ratios at 0.9 demand level, with $\psi = 0.5$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	0	1.65	1.21	1.18	1.16	1.16
5	2.19	1	1.04	1.04	1.14	1.14
10	0.63	0.98	1.04	1.04	1.06	1.07
20	0.52	0.95	1	0.99	1.01	1.02
100	0.83	0.98	0.97	0.99	1	1

Table 3.3: DOL ratios at a demand level of 1, with $\psi = 0.5$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	0	1.09	1.34	1.32	1.2	1.23
5	1.9	1.08	1.03	1.11	1.2	1.2
10	0.65	0.99	1.1	1	1.18	1.17
20	0.54	1.02	1.06	0.83	1.09	1.1
100	0.77	1	1.04	0.86	1	1

Table 3.4: DOL ratios at 1.3 demand level, with $\psi = 0.5$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	0	1.33	1.08	1.13	1.17	1.26
5	1.64	1.11	1.16	1.17	1.22	1.22
10	0.55	1.17	1.18	1.19	1.24	1.23
20	0.65	1.03	1.18	1.18	1.23	1.23
100	0.77	0.99	1.08	1.1	1.17	1.18

Table 3.5: DOL ratios at 0.7 demand level, with $\psi = 1 \pm 0.1$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	7.96	1.09	1.1	1.05	1.11	1.16
5	1.86	1.12	0.97	1.01	1.05	1.04
10	1.01	1	1.01	1.01	1.01	1.02
20	0.92	1.08	0.99	1	1	1
100	0.86	0.99	1	1	1	1

Table 3.6: DOL ratios at 0.9 demand level, with $\psi = 1 \pm 0.1$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	4.04	1.71	1.05	1.3	1.18	1.19
5	1.48	1.17	1.12	1.1	1.15	1.15
10	0.97	0.99	1.01	1.03	1.07	1.08
20	1.06	1.09	1.01	1.01	1.02	1.02
100	0.92	1.01	1	1	1	1

Table 3.7: DOL ratios at demand level of 1, with $\psi = 1 \pm 0.1$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	14.21	1.69	1.32	1.13	1.3	1.22
5	0.67	1.37	1.36	1.15	1.22	1.25
10	1.19	1.09	1.09	1.09	1.18	1.2
20	0.95	0.97	1.09	1.02	1.1	1.1
100	0.90	0.99	1.05	1	1	1.01

Table 3.8: DOL ratios at 1.3 demand level, with $\psi = 1 \pm 0.1$. Rows represent agent counts and columns represent task counts. Normalized based on performance of standard genetic threshold model ($\psi = 0$).

	2	10	50	100	500	1000
2	17.26	1.63	1.53	1.38	1.27	1.29
5	0.69	1.03	1.22	1.25	1.32	1.29
10	1.05	1.08	1.13	1.24	1.27	1.28
20	0.76	1.05	1.15	1.22	1.24	1.26
100	0.85	1.05	1.06	1.1	1.15	1.18

Notice that social influence increases the level of specialization, shown by cell numbers greater than 1. Even when demand level is lowest at 0.7, when social influence is expected to be lowest according to our tested parameters, there is still a general increase of specialization. Also notice that the effect of social influence also increases as the number of agents increase. Finally, it's visible that the effect also increases as the demand level increases.

Note the general growth of the ratio as we move from a demand level of 0.7 through to a demand level of 1.3. This is in spite of the fact that division of labour is known to drop significantly (almost nil) as demand levels exceed 1. We set the value of the cell at 1x1 to 0, as the level of specialization was so low that it rendered any meaningful comparison meaningless.

When demand level is below 1, agents have fewer specializations that will have enough stimulus to surpass their thresholds. As lower stimulus lead to more inactive agents, the chance of these agents suddenly coming upon multiple tasks that were under-worked is slim. We expected little to no increase from social influence here. This is due to the fact that social influence only plays a role when an agent has multiple specializations from which to choose. The results indicate that even when there is low demand, enough agents are still faced with multiple choices, resulting in an specialization from social influence.

When the demand level is 1, the amount of stimulus added is exactly equal to the amount of work able to be performed. Excess stimulus only remains when agents are not properly tasked - either because they are inactive, or on a task which doesn't have enough work for them to perform. There will be a few agents that are misplaced (inactive or under-productive), resulting in a slight increase in the level of excess stimulus per iteration. This situation will lead to more agents having multiple tasks above their threshold level. This causes a further increase in specialization than that seen at the lower levels.

A demand level above 1 indicates that even if all agents are active and fully worked, they are not able to satisfy all the stimulus in the system. As the level of excess stimulus increases per iteration, agents will have more tasks available that surpass its threshold. When an agent's neighborhood remains consistent - where its neighbours are maintaining their specialization, there is a higher probability of it choosing the more popular tasks, as determined by its neighbours. We found that while specialization was very low when demand level was above 1, there was still an increase from social influence.

Because the choice that an agent makes is based on a probability, there still remains a chance that an agent will choose a specialization that none of its neighbours have chosen. As this will in turn influence those neighbours decisions, its possible that in a few cases

Table 3.9: Result of other social influence rate strategies compared to fixed rate of $\psi = 0.5$ when ran over 1200 experiments

Specialization	$\psi = 0$	$\psi = 0.1$	$\psi = 0.2$	$\psi = 0.3$	$\psi = 0.4$
Increased	384 (32.0%)	404 (33.7%)	395 (32.9%)	430 (35.8%)	481 (40.1%)
No change	112 (9.3%)	2 (0.2%)	0	0	0
Decreased	704 (58.7%)	794 (66.2%)	805 (67.1%)	770 (64.2%)	719 (59.9%)

social influence may actually decrease specialization over a short period of time. This is especially pronounced in small networks, as the effect of choosing new specializations will cascade more quickly, having a greater effect on the entire network. We believe this to be the explanation for the cases in our experiments where there is a reduced level of specialization where an increase is expected.

We also noticed that agents striving to "follow the Joneses" when choosing specializations also result in a sort of topology based caste system. In cases where demand level is significantly above 1, agents will tend more to choose the same specializations as their neighbours. This has a cascading effect, as one agent changing its specialization will influence its neighbours to also follow suit. In the extreme case where tasks have more stimulus than can be performed by all agents, the result will be that all agents may converge upon performing one task. Even when all agents have converged, there is still a chance that an agent may choose a specialization not performed by any of its neighbours, even if all agents are directly connected. We can deduce that the likelihood of convergence is also dependent upon the connectivity of the social network. The more neighbours an agent has, the more influence exerted upon its decisions.

3.6.2 Comparison to fixed rate of $\psi = 0.5$

When ψ is at a constant level below 0.5 performance is worse than our baseline ($\psi = 0.5$). This can be seen in Table 1. There is a pattern of increasing performance levels also visible in Table 1, with the exception being the small drop going from $\psi = 0.1$ to $\psi = 0.2$. This

Table 3.10: Result of other social influence rate strategies compared to fixed rate of ψ = 0.5 when ran over 1200 experiments

Specialization		$\psi = 0.6$	$\psi = 0.7$	$\psi = 0.8$	$\psi = 0.9$	$\psi = 1.0$
Increased		718 (59.8%)	752 (62.7%)	785 (65.4%)	799 (66.6%)	796 (66.3%)
No change		0	0	0	0	0
Decreased		482 (40.2%)	448 (37.3%)	415 (34.6%)	401 (33.4%)	404 (33.7%)

Table 3.11: Result of other social influence rate strategies compared to fixed rate of ψ = 0.5 when ran over 1200 experiments

Specialization		$\psi = 0.2 \pm 0.1$	$\psi = 0.3 \pm 0.1$	$\psi = 0.4 \pm 0.1$	$\psi = 0.5 \pm 0.1$	$\psi = 0.6 \pm 0.1$
Increased		379 (31.6%)	362 (30.2%)	403 (33.6%)	645 (53.8%)	647 (53.9%)
No change		113 (9.4%)	137 (11.4%)	151 (12.6%)	174 (14.5%)	149 (12.4%)
Decreased		708 (59.0%)	701 (58.4%)	646 (53.8%)	381 (31.8%)	404 (33.7%)

Table 3.12: Result of other social influence rate strategies compared to fixed rate of ψ = 0.5 when ran over 1200 experiments

Specialization		$\psi = 0.7 \pm 0.1$	$\psi = 0.8 \pm 0.1$	$\psi = 0.9 \pm 0.1$	$\psi = 1.0 \pm 0.1$	$\psi = 0.5 \pm 0.5$
Increased		699 (58.3%)	743 (61.9%)	753 (62.8%)	761 (63.4%)	571 (47.6%)
No change		136 (11.3%)	120 (10.0%)	105 (8.8%)	109 (9.1%)	172 (14.3%)
Decreased		365 (30.4%)	337 (28.1%)	342 (28.5%)	330 (27.5%)	457 (38.1%)

pattern is also evident in Table 2, where again there is an exception with a small drop going from $\psi = 0.9$ to $\psi = 1$. There is also a pattern of increasing levels of specialization while ψ continues past 0.5.

When we compare $\psi = 0.5$ with a varying rate of $\psi = 0.5 \pm 0.1$, we see that varying rates between agents produce higher performance, even when they still average the same. Specialization levels also increase as the social influence rate increases when using varying rates. There is a drop going from $\psi = 0.2 \pm 0.1$ to $\psi = 0.3 \pm 0.1$, with this being the only exception. $\psi = 0.5 \pm 0.1$ produces higher levels of specialization than $\psi = 0.5 \pm 0.5$, which suggests that increasing the variance rate does not produce more specialization.

In our previous work, we demonstrated the increase of specialization levels by comparing results when $\psi = 0.5$ and $\psi = 0$ (genetic threshold model). We presented these results over a varying range of agent counts and task amounts. The values tested were the same values tested in our present experiments. These are presented again below in Tables 5-8. To highlight the increase in performance resulting from increasing ψ, we present the result of our comparisons of $\psi = 1 \pm 0.1$ with $\psi = 0$. These can be seen in Tables 9-12. We can see that $\psi = 1 \pm 0.1$ produces higher specialization than $\psi = 0$ in the vast majority of cases, even across different parameter settings. This further reinforces our finding that increasing the social influence rate will lead to increased specialization.

3.7 Conclusion and future work

In this study we examined the effects of a social influence strategy on an agent's choice of specialization. We found that social influence increases division of labour when there is an excess of demand. When influenced by their peers, agents become more specialized when there is too much task choice available. Our results reinforce the findings of previous research that indicate that specialization increases as group size and task number increases, which is also found in human societies [7]. Our research further shows that in such settings, social influence increases the level of specialization above and beyond the increase from those factors. It can also be concluded that increasing the influence rate lead to increases in the level of agent specialization. This was found to be true in cases where agents shared the same constant influence rate, and cases where agents had varying influence rates.

While it is possible still to increase ψ beyond a value of 1, we don't think it wise to do so. The higher the value of ψ, the higher the likelihood that an agent will choose a specialization from those chosen by its neighbours. Given a system with a large number of tasks and a small level of agent connectivity, agents are much less likely to choose tasks not being performed by others. While this will result in a higher level of specialization, the counterpoint is that there will be a reduced level of diversity. More agents will be performing the same tasks. If a specialization has an effect on system resources, then this may result in one resource becoming depleted rapidly. This is in spite of the fact that agents will only perform specializations while demand exists. Demand may exist for items that are in danger of depletion, such as oil is in the real world.

In the future, we would like to investigate the effect of social influence on stimulus perception. In this paper, the effect of social influence after a task has already surpassed the agent's threshold. We would like to study the idea that if more of our neighbours are performing a task, it becomes "cooler". The underlying idea being that such an effect may reduce an agent's innate threshold for that task, allowing them to perform tasks which they may not have if they were not influenced. Furthermore, it would be interesting to examine other social strategies for division of labour, perhaps with the goal of comparing these to find the most effective. One such idea is to investigate the desire of agents to find niches. We are interested in studying what effect the drive to be different has on division of labour. This was addressed in [53], where agents chose their specialization based on the result of a function that weighs both their threshold levels and inverse social influence. We believe that there is more room for investigation with regards to that approach. In keeping with that view, we would like to compare these different approaches, perhaps even hybridizing them, to understand the effect.

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Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants*. Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 – 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f3705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

Chapter 4

WASPS: A Weight-Allocated Social Pressure System for the Emergence of Agent Specialization

4.1 Preface

This unit is the most fundamental in this dissertation. In here we create an overarching computational framework for the emergence of agent specialization. We abandoned the idea of positive social influence, instead using social inhibition as found in several other works. We do bring the idea of an influence rate, discovered in our previous work. We also expanded the scope for agent specialization to a couple other scenarios. We are able to handle agents choosing to divide their resource (time used primarily, but not required), as opposed to giving it all to one task. We were also able to handle agents having different levels of skill for each task (this variability influenced by our previous work, and the variability of the influence rate). These were rather significant scope expansions, as our approach was now able to handle heterogeneous agent environments in the emergence of specialization.

We were able to demonstrate that this approach leads to the increase in agent specialization given random populations. There was no attempt to claim that it would create the optimal level of specialization for a population, as we could quite clearly demonstrate that given our goal of handling different skill levels, it would be possible to create a population that was fully specialized, but with every agent performing the task they are least skilled at. In such a scenario, our methodology would result in a reduction of specialization levels, but better specialized agents. Better would be in the sense that they are performing tasks they are more skilled at.

4.2 Introduction

Specialization is where individuals produce goods and services beyond local or personal need, depending upon other individuals to supply other needed goods. There are many varying definitions of specialization, with most taken from the archaelogical, biological and economic fields. One definition from archaeology is that specialization is "the production of substancial quantities of goods and services well beyond local or personal need, and whose production is generally organized, standardized and carried out by persons freed in part from subsistence pursuits" [1]. By choosing to specialize, specialists must obtain some or all of their subsistence goods through exchange with others [16]. There are varying levels of specialization, ranging from being able to sustain oneself, while simultaneously producing goods for the consumption of others, to complete dependency upon exchange with others for subsistence goods. Dependence upon others for subsistence was viewed by Childe as the essence of economic specialization [11].

Specialization allows individuals to maximize their productivity by exploiting their environment [37], and occurs because entities belong to a community of mutual interest, cooperating to serve that mutual self-interest [48]. Specialization may be assigned, as in caste systems, or chosen by an individual driven by varying means, including genetic, social and economic. Another term for specialization is division of labour, which is defined by Hollbloder as "...when individuals can be turned into specialized working machines, an intricate division of labour can be achieved and a complicated social organization becomes attainable even with relatively simple repertory of individual behaviour" [21].

There are both internal and external factors that influence an individual's choice of specialization [5]. Internal factors include genetic, neural, hormonal and experience elements. External factors include economic factors such as demand (stimulus) and social influences [25, 40, 45]. It seems that no single behavioural model may fully explain division of labour in complex systems [50]. Different models and approaches have different assumptions, which makes it particularly difficult to compare the effects of factors across different approaches.

The study of specialization is important to several fields. For instance, archaeologists study specialization to understand the changes in societies as a result of the emergence of specialization. It also gives insight into why individuals would choose to produce certain goods over others. From the biological perspective, specialization helps to explain the behaviour of biological creatures such as ants, wasps and bees [32, 40, 42], which have been empirically shown to specialize based on tasks. Economically, specialization is studied to understand its effect upon a society's economy. It further serves to study how a market may grow or contract based on the specializations present, as these specializations lead to increases in the productivity of market systems [37]. Allyn Abbot Young points out that a productive individual increases the supply of certain commodities, while simultaneously increasing the demand for others [55]. In spite of its role in economics and biology, little is known of the origins and causes of specialization and exchange [4].

In this paper we focus on the social approaches to artificial agent specialization. Here we define an agent as an autonomous social party that can perform several tasks with varying levels of skill. Being social, these parties can also be influenced by their peers across their social networks. It is our hypothesis that competition will drive agents to allocate more of their resources to produce goods with which they possess a comparative advantage in relation to their competitors. As the primary differentiator of efficiency in our model is skill, it can be assumed that more skilled agents will have a comparative advantage over their less skilled competition. In this individual based model, these self-interested agents will be influenced towards performing tasks that will maximize their own productivity. We believe this approach will lead to significant increases in the overall level of specialization within an agent population. In the next section we introduce the social inhibition model from which this work is primarily inspired. We then describe our generic model that uses weight-based allocations. Finally, an experimental setup is presented and discussed with concluding remarks.

4.3 Social Inhibition

There are several social models for the emergence of agent specialization. One such method is social inhibition, which implies that as agents choose their specialization, they notify other agents that they have done so, reducing their desire to also choose this specialization. To put that idea in economic terms would be that choosing a specialization reduces the demand (stimulus) for that specialization. Social inhibition aims to explain concepts such as temporal polyethism, which is division of labour based on age, as a result of the interaction between behavioural development and the inhibitory effects of other workers [5, 22, 38]. Temporal polyethism can also be explained experientially, as older agents would have more experience, and thus more knowledge upon which to base their actions [43]. This model is more concerned with the physiology of workers and their interactions. Initially, the model took the form of an activator-inhibitor approach, whereby all agents would eventually mature to perform specific tasks, but inhibitors from current performers of these tasks would slow their activation.

Naug and Gadagkar presented a social inhibition model that aimed to explain the age polyethism in wasp species [38]. Their model was in turn based on the verbal model of Huang and Robinson [22]. In Naug and Gadagkar's model, each agent has two pods: one that increases its own preference for a task, and another that inhibits the preferences of agents it interacts with for the same task. Their model claimed that individual specialization is emergent from the increase in activator due to age, as well as the amount of inhibitors exchanged when agents interact. The model assumes that all agents possess the same preference and skill level for task performance, which makes it difficult to adapt to situations such as those we aim to address.

The effect of competition on task specialization was examined in [35]. Competition was shown to lead to the occurence of specialists as an emergent phenomenon dependent on the size of colonies. Their model was based on a genetic preference model though, whereas our model is based on social interactions. They also studied differing demands for tasks, something which we do not explore here.

Another social interaction model was explored in [18]. Agents had an active and inactive state for the four tasks in the model. The agents communicate with each other, giving them some idea of how many other agents are performing the same task. These interactions between agents is designed such that the system will trend toward a stable set-point where there is a balance of active and inactive agents for each task. Like the above mentioned models, they also assume that agents do not possess an innate preference or skill for tasks.

A non-social model that is also relevant is [33]. Lavezzi's model shows that the amount of specialization and level of per capita output depends on competition, agent connectivity, agent thresholds, and initial conditions such as number of agents and their connectivity. An agent's potential to choose a specialization is limited by the amount of other agents performing the same task, as well as the stimulus level for that task. Agents of course have to know about the level of competition, or be directly aware of the changing stimulus levels. In either of these two situations, agents are required to have excess knowledge of their economic environment. While non-social, we have found that a lot of the effects claimed by Lavezzi are also evident in our model.

The existing social models have several other shortcomings, several of which we look to address. In these models, agents are only able to perform one task per unit of time. In our model, we aim to deal with situations where agents can divide their time among several tasks. Take for example something like human agents, such as those found in [30], who have several tasks to perform in each year such as farming, hunting, getting water and getting wood.

In the social inhibition model, which is aimed at age based specialization, the social influence of other agents do not directly determine the specializations that others will choose. Tasks must first be ranked in a way related to age, then agents are ranked by fit for those tasks. After that, agents are then assigned based on the number of workers needed for that task. We think that while this may be appropriate in insect colonies, it makes the model difficult to adjust to agent populations where tasks may not have priorities. In our model, we assume no priority among tasks.

4.4 Approach

Our approach is not aimed at system optimization, whereby the system itself tries to be the most productive possible. Instead, agents should be able to emerge the specializations that they are most suited for in their given environment. We assume the existence of a set of tasks T. Each element *t* in T is a task that can be performed by an agent. Each agent has a level of skill associated with each task. The skill level may be static, or it may be determined by the agent's previous success at performing the task. This allows for skill levels that may correspond with fitness functions in evolutionary algorithms. This skill level is quantifiable, comparable and monotonic, such that $sk_a(t) > sk_b(t)$ means that agent *a* is more skilled than agent *b* at performing task *t*. All agents assume they can perform the task perfectly. The level of skill is then reflected in the amount of inhibition that agent then releases when they interact with others. Agents are thus able to determine their true relative skill level through interactions with other agents. The strength of inhibition, which we refer to as the influence rate, depends on each agent.

In our test simulations, we assume that all agents have the same level of influence. This is not required, and it is quite possible for different levels to make sense in a domain. For instance, we can create the effect of age polyethism if we were to have the influence rate grow with age. In that case, to create task prioritization, we can have the level of influence vary by task as well. In addition to skill, agents have to divide their time among tasks. They therefore need to track their allocations, which they do internally. Note that while we refer to time, that is simply one idea of a resource. This model does not require the resource to be time, but it can by money, food, or any other divisible resource. The simulation is composed of a set of interacting agents within a social network that can all perform the same tasks at varying skill levels.

4.4.1 Problem Description

Given agent Ag, the set of tasks available to Ag T_{Ag} and a resource R_{Ag}, how does an agent allocate its R_{Ag} among each task t in T_{Ag}? So, $\Sigma x_i = S(R_{Ag})$, where i is each task in T_{Ag}, $S(R_{Ag})$ refers to the amount of the resource R_{Ag} available, and x_i refers to a fraction of $S(R_{Ag})$. The problem also involves the following conditions: The problem is continuous over a period of iterations, $S(R_{Ag})$ changes between iterations and x_i is allowed to change over iterations.

4.4.2 Weight-based model for resource allocation among tasks

For each agent Ag, we propose a set ALLOC, where $e_i \in ALLOC \Rightarrow$ there is a task i in T_{Ag} and e_i represents the weight allocated to task i. Task weights in ALLOC are relative, therefore for a given task i and a resource to be allocated R_{Ag}, the amount of R_{Ag} to be allocated to task i is: $\frac{e_i}{S(ALLOC)} \times S(R_{Ag})$, where S(ALLOC) is the sum of all elements in ALLOC. We make no assumptions about the initialization of the weights in ALLOC; they can be randomly assigned, or initialized by some other method. A task having a weight of 0 will result in the task being allocated none of R_{Ag}. For simplicity, we will assume R refers to time for the rest of this paper. We also normalize the weights in ALLOC such that S(ALLOC) is always equal to 1.

4.4.3 Model outline

Agents influence other agents when they interact. In some networks, such as kin network, it can be assumed that they interact with all their neighbours in each time step. The amount of influence is dependent on skill level. The higher the skill level, the higher the level of influence. When an agent interacts with another, it positively reinforces its own behaviour, while also inhibiting the other agent. The amount of self-reinforcement is the same amount that it inhibits the other agents. After all agents have interacted, the agent subtracts the level of inhibition it has received from the level of activation it has provided itself. The agent also self-activates itself, such that an agent that does not interact with any other agents will still change its behaviour. These effects result in the change of the allocation levels for the agent.

4.5 Agent Properties

4.5.1 Agent Attributes

Each agent has the following attributes:

- An allocation set ALLOC = { ti <- [0,1]}, for all tasks $i \in T$, where ti is the fraction of time the agent will spend on task *i*.
- A skill set SKILL = { si <- [0,1]}, for all tasks $i \in T$, where *si* is the skill of the agent at performing the task *i*. If an agent cannot perform a task *p*, then the value of *sp* would be 0. The skill level for a task may be dynamic and updated regularly. The skill value as a function must be monotonic though, such that if agent *Ag1* has *si* 0.5 and agent *Ag2* has *si* 0.7, then we can say that *Ag2* is better than *Ag1* at performing task *i*.
- A set PODS = { pi }, for all tasks $i \in T$, where *pi* is a 3-tuple (A, SA, I). In this 3-tuple for task *i*, *A* represents the activator store for the agent, *SA* is the level of self-activation, and *i* is the inhibitor store for the agent. The agent will increase the weight of the associated task when $A+SA > 0$, and decrease it when $A+SA < 0$.

The idea behind self-activation is the inclination of an agent to perform more of the task at which they are best. This value should be large enough that it will allow an isolated agent to specialize over a long period of time, but it should also be small enough that it doesn't overwhelm the social pressure created by stronger competitors.

4.5.2 Agent Inhibition

The level of inhibition in an agent's pod for a task *i* is determined by several factors:

- The skill level of the agent at performing task *i*.
- The size of the agent's social neighbourhood.
- The influence rate, *IR* = (0, 1], which is a parameter that determines the strength of an agent's influence. This parameter can be universal, or variable for each agent. It is also possible that the influence rate can be different for each task. We can re-create the effect of polyethism if we were to make *IR* dependent upon the age of an agent.

4.5.3 Agent interaction

When agents *Ag1* and *Ag2* interact, for each task $t \in$T, we obtain the values in *Ag1*'s pod *pt* for task *t*, and *Ag2*'s pod *pt* for task *t*. The value in *Ag1*'s *A* will be decreased by *Ag2*'s I and vice versa. Each agent will also increase its own *A* by its *I*.

Since agents both exchange inhibition, and inhibition level is tied to skill and influence level, the more skillful and influencial agent would have a greater effect on a neighbour than a less skillful and influential competitor. While the influence of the "better" agent would be stronger, the weaker agent would still inhibit the stronger one. This method allows agents to exchange influence each other only when they interact. It is also possible for agents to be considered to interact on every iteration, in which case agents would inhibit all others in their neighbourhood.

4.5.4 Agent Attribute Updates

During each time period, agents will have performed their tasks based on their allocation weights (ALLOC). If the skill set is dynamic, then it would be updated based on the results of task performance. The influence rate of each agent would also need to be updated. If agents have different influence rates for each task, then the updates would need to be applied for each task.

Agents will then update their allocations based on each task pod. Given an allocation ti for a task i, and a pod (a, s, x) for the same task i, then ti will be updated as:

$ti = ti + a + s$. That means that the amount of self-activator s will be added to the activator a, and the sum of that added to the current weight. After all task weights are updated for an agent, the values are again normalized, resulting in the sum of all weights being 1.

4.6 Experiments and Results

To measure the level of specialization within a population, we use a measure developed in [19]. The measure quantifies the degree to which agents in a population are specialized. We have each agent record their task allocation amounts. These amounts are then stored in an nxm matrix, with n being the number of agents and m the number of tasks. We then normalize this matrix such that the sum of all cells is 1. The mutual information and Shannon entropy index [47] are then calculated for the distribution of individuals across tasks. Finally, dividing the mutual information score by the shannon entropy score will provide a value between 0 and 1. A score of 0 indicates a population with no specialization, while a score of 1 indicates a fully specialized population [19].

We test our method across several parameter types. These are: the type of network, the number of tasks, the number of agents, and the influence rate. We test with two network types, small-world networks and random networks. Small-world networks[36] are networks whereby most nodes are connected by a small degree of separation, with the existence of a power-law structure among many nodes. Two famous examples of a small-world network are the '6-degrees of separation' phenomenon found within the US population [36] and a similar phenomenon among many sites on the World-Wide Web [9]. With random networks, each node will just be randomly connected with another node. We use the same amount of total edges in both network types, dependent upon the number of agents.

We tested for 2, 4, 10 and 20 tasks. Most studies involve 2 to 5 possible tasks [53], while some insect colonies have anywhere from 20 to 40 specializations [5]. Although we could have tested for more possible tasks, we observed that 20 would be sufficient to demonstrate the process. As for the number of agents, we tested smaller groups of 10, 50 and 100 agents, as well as larger groups involving 500 and 1000 agents. Each agent acts after the previous step for all others, meaning that all agents operate in the same time step. Tasks are all assumed to take the same amount of time to perform. We tested with a variety of influence rates, these being 0.05, 0.1, 0.25 and 0.5. The influence rate was the same for all agents during each run. We used a constant self-activation rate of 0.05. All agents also have the same capacity for task performance, that is to say the same amount of time available to be allocated. We ran each combination of parameters 10 times.

Each agent would be created with random task allocations. Thus for each available task, the agent would assign a percentage of their time to be spent on that task. As the metric developed in [19] is dependent upon these task allocations, different populations of agents would necessarily have different initial levels of specialization. As such, it is not possible to compare the initial and ending specialization levels across runs within the same network type, even with the same parameter settings. The initial populations would be the same for different network types when all other parameters are the same. Considering these conditions, we measure the change in the level of specialization over a run. In the tables given, rows represent the number of tasks and columns represent the number of agents. Tables 1 through 4 illustrate a representative sample of our overall results. They report the average division of labour (DOL) and standard deviation with influence rates (IR) of 0.05 and 0.5 for both small-world and random networks. The DOL values are average multiples of the initial level of population specialization over the 10 runs for each parameter

	10	50	100	500	1000
2	3.3 ± 1.24	2.48 ± 0.41	2.43 ± 0.29	2.28 ± 0.16	2.28 ± 0.10
4	3.46 ± 0.95	2.86 ± 0.28	2.54 ± 0.24	2.53 ± 0.08	2.48 ± 0.12
10	3.07 ± 0.65	2.73 ± 0.31	2.64 ± 0.11	2.69 ± 0.07	2.71 ± 0.06
20	3.36 ± 0.42	3.08 ± 0.29	2.9 ± 0.26	2.92 ± 0.12	2.88 ± 0.08

Table 4.1: Average DOL multiple and standard deviation with IR = 0.05 in Small-World Networks.

	10	50	100	500	1000
2	3.82 ± 2.11	2.76 ± 0.36	2.69 ± 0.35	2.48 ± 0.16	2.53 ± 0.11
4	4.39 ± 1.46	3.4 ± 0.43	3.15 ± 0.18	3.09 ± 0.06	3.03 ± 0.15
10	3.74 ± 0.80	3.4 ± 0.47	3.35 ± 0.16	3.43 ± 0.09	3.45 ± 0.06
20	4.54 ± 1.06	3.53 ± 0.35	3.73 ± 0.32	3.72 ± 0.14	3.72 ± 0.11

Table 4.2: Average DOL multiple and standard deviation with IR = 0.5 in Small-world Networks.

combination. Thus a value of 3.3 indicates that there was a 230% increase in the level of specialization. For brevity, the results of other influence rates are not shown.

The level of specialization increased in all 1600 runs that we simulated. In our small-world networks, the average result was a multiple 3.2 over the initial values, with a standard deviation of 0.75. With our random networks, the average result was a multiple of 3.9, with a standard deviation of 0.97. We believe that the higher increase in our random networks is due to the higher average number of connections between agents. In small-world networks, several agents have a lot of neighbours while most have only a few. As agents are influenced by interacting with others, having more interactions result in each agent moving toward its optimal state faster. This suggests that increasing the level of connectivity between agents will result in more pronounced increases in specialization.

	10	50	100	500	1000
2	4.42 ± 2.2	2.95 ± 0.5	2.95 ± 0.37	2.82 ± 0.11	2.83 ± 0.14
4	3.62 ± 1.02	3.06 ± 0.33	2.93 ± 0.27	2.92 ± 0.11	2.91 ± 0.09
10	2.99 ± 0.47	2.75 ± 0.24	2.88 ± 0.1	2.87 ± 0.08	2.88 ± 0.05
20	2.99 ± 0.27	2.81 ± 0.16	2.83 ± 0.11	2.83 ± 0.06	2.81 ± 0.04

Table 4.3: Average DOL multiple and standard deviation with IR = 0.05 in Random Networks.

	10	50	100	500	1000
2	5.34 ± 2.79	3.79 ± 0.74	3.65 ± 0.43	3.57 ± 0.16	3.59 ± 0.15
4	5.04 ± 1.57	4.48 ± 0.37	4.23 ± 0.29	4.34 ± 0.13	4.28 ± 0.12
10	4.98 ± 0.70	4.65 ± 0.27	4.79 ± 0.2	4.81 ± 0.12	4.83 ± 0.08
20	5.25 ± 0.35	4.84 ± 0.13	4.92 ± 0.19	4.93 ± 0.08	4.91 ± 0.05

Table 4.4: Average DOL multiple and standard deviation with IR = 0.5 in Random Networks.

Our results may be depressed by the emergence of equilibrium states within our populations. This is the case when adding more iterations will not result in any increase in the population's level of specialization. This emergence of equilibrium states is not surprising though as it is predicted in [55]. As the initial level of specialization is randomly between 0 and 1, it is the case that a population with a high initial level of specialization would not have much room for improvement. We would not expect to see a state of equilibrium if we had used a dynamic society, as new births, deaths, and other state changes would keep the situation in a state of flux [33].

We noticed that in many cases agents would not become fully specialized. This may be in spite of the fact that they may be significantly better at a particular task than all competitors. This is because they would still have some pressure to perform other secondary tasks where they may still have some advantage. This became more pronounced as the number of tasks increase. In such cases, agents may possess comparative advantages in multiple tasks, and thus the motivation to increase their allocation in both. As the allocation system is weighted, the increases in both weights offset each other.

While we did notice that in most cases increasing the level of influence would also result in a higher level of specialization, this not not occur in all cases. In our simulations, the level of specialization would decline in many cases when going from an influence rate of 0.25 to one of 0.5. Because of the different initial populations and specialization levels, we are unable to study the effect of changing agent and task amounts.

4.7 Conclusion and future work

In this paper we presented a new social inhibition model for the emergence of specialization in agent societies. We showed that this model is able to significantly increase the level of specialization in a random population. While several current models deal with domains where agents can only perform one task at a time, our model deals with having agents that have to allocate their time among several tasks. We have shown that when agents are differentiated by skill level, competition and social inhibition can be used to increase division of labour. We found that our agents will increase their allocation of time among tasks for which they possess a comparative advantage over their neighbours. This follows a well established law of economics. Surprisingly, we also found that using our weight based approach, agents will not necessarily specialize on the task they are most efficient at. This is because the change in allocations for multiple tasks may offset each other. The result seems supported by real world experience, where we have yet to see a modern nation completely specialize on one product. Our model is created in a way that makes it applicable to many domains.

We intentionally created the model in the abstract because we would like to keep it general. Many of the parameters used can be changed to accomodate different domains. We also didn't state how it is that agents interact for the same reason. Interaction could be either broadcast, exchanged through the environment, or exchanged through message passing.

The meaning of the social network and its connections is also left open intentionally, such that it could represent a wide range of topics, such as a topographical neighbourhood, or even a collaboration network.

We currently do not account for different levels of resource availability. We would like to investigate what changes if any the model would need to work under those conditions. In addition, we assume that demand is always equal to the amount of a resource produced. It would be a good idea to investigate different levels of demand either globally or locally for each task. We would also like to see how the model performs under dynamic environmental conditions. We would like to apply the model in concrete domains such as human society simulations, or even social insect simulations. We believe that this model can encompass several of the currently existing social interaction models, including the social inhibition model which inspires it. We didn't think it appropriate to compare our approach to the social inhibition approach here though because they have different assumptions.

Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants*. Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 – 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f3705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

Chapter 5

A Genetic and Social Computational Model for the Emergence of Skill-Based Agent Specialization

5.1 Preface

This unit builds upon the previous chapter. The computational model created there is taken in new directions. The result of this is that a lot of the assumptions we had previously held in the creation of the WASPS model no longer hold. One such example is the name; WASPS stands for Weight-Allocated Social Pressure System. In this unit, weights are replaced by thresholds as found in the genetic threshold models. Nonetheless, we were able to maintain the majority of items from the WASPS model, and in a sense redefine it to accomodate new discoveries from this unit.

In this variation of the computational model, agents are still heterogeneous. On the individual learning level, agents possess a natural equilibrium threshold to which they seek to navigate. In existing genetic threshold models, it is accepted that the threshold levels will change, therefore, we are not doing something out of the ordinary here by allowing the same. In addition to the individual pull that agents possess, they are affected by competition from other agents performing the same task. The result is that an agent may be lead to change its threshold away from its equilibrium. Agents that were inactive during an iteration would reduce their threshold for each task, with the hope of becoming active again. Note that this would likely give an inefficient agent only small chances of becoming active, as their thresholds would spike back up when faced with competition from much more efficient neighbours.

We also introduced a metric that we labeled Quality of Work (QOW). This was a measure of the average level of skill of all agents performing a given task. Our results were able to show that we can get a high QOW using this model, but at the cost of a lower level of specialization. This is in keeping with the argument made in the preface of the previous unit, where we said that it would be possible to have a lower level of specialization using our method. It is in our view not usually the goal to simply have specialization for the sake of specialization, but preferably higher quality specialization. This variation of the computational model, and WASPS itself, stays true to this goal.

5.2 Introduction

Specialization, also called division of labour, has several definitions, often depending upon the field and context in which it is being used. For this paper, we define specialization as the spending a disproportionate amount of a resource upon one purpose when compared to other available purposes. Based upon this definition, specialization must be seen as a spectrum, ranging from completely providing for oneself, while also producing for the consumption of others, to being completely reliant on others for meeting one's needs. According to [11], this reliance upon others for the meeting of needs is the essence of economic specialization. In cases where individuals would need the other purposes to be met, they would have to rely upon others to assist them in meeting those needs [16].

In populations of heterogeneous individuals, it can fairly be presumed that these individuals possess different aptitudes for available tasks. When these individuals specialize based upon their differing aptitudes, they are potentially able to maximize their productivity by exploiting their environment [37]. This is in cases where their exists a community of mutual interest, whereby other individuals are also aiming to maximize their own productivity in relation to competitors [48].

There are different ways to cause the emergence of specialization within complex systems. It may be assigned, such as seen in caste systems, or it can be chosen by individuals. This choice can be affected by several factors, including genetic, social and economic considerations [5, 25, 40, 45]. No one model can fully explain specialization in complex systems [50]. As such, most models work with their own assumptions and contexts. The different assumptions in these models makes it particularly difficult to compare results across approaches [14]. In spite of the importance of specialization in many fields, there is still little known of the origins and causes of specialization and exchange [4].

We will be using the term individual and agent interchangeably in this paper. We define an agent as an autonomous social party that can perform several tasks with varying levels of skill[14]. These social individuals can be influenced by other individuals within their social networks. As[14] showed, agents are able to increase their specialization in tasks where they have larger comparative advantages over other agents within their social network. They were able to demonstrate significant increases in agent specialization when agents with varying skill levels for tasks were able to influence the specialization decisions of other agents. As in that paper, we also assume the same characteristics of agents; that being their possession of varying skill levels for each task, as well as their ability to divide a given resource among those tasks.

In this paper, we seek to emerge specialization based on competition. The effect of competition on task specialization has been in examined in [35]. Competition has been shown to lead to the emergence of specialists, dependent upon the size of colonies [23, 35]. Lavezzi showed that the amoutn of specialization and level of per capita output depends on many factors, including competition [33].

In the next section, we present background on major existing models for the emergence of agent specialization. We present the Genetic Threshold Model, Social Inhibition Model, and the more recent Weight-Allocated Social Pressure System (WASPS) model. We then show how to mimic the behaviour of both the Genetic Threshold and Social Inhibition models by modifying the WASPS model. We then present a hybrid variant, inspired by the WASPS model, that mixes both the genetic and social models to deal with a population of agents with genetic thresholds, who can also inhibit less efficient agents in the performance of available tasks. We finally present our results and give our conclusions and future plans.

5.3 Background

5.3.1 Genetic Threshold Model

The genetic threshold model posits that there is a certain level of stimulus for a task that must be reached before an agent will choose to perform that task [45]. This threshold varies between agents. This proposition has been backed up empirically in the study of social insect societies, such as ants and bees [17, 40]. Agents will perform no tasks if none of the stimuli for all available tasks fail to cross its response threshold [5]. The stimulus for a task will decrease when that task is performed by an agent.

The level of stimulus present in a given environment is dependent upon the context being investigated. In some environments, agents are able to perceive the same level of stimulus, while in others, the level of stimulus perceived is dependent on other factors related to the agent. Using this model, it is possible for caste systems to emerge when certain agents tend to have particularly low thresholds for certain tasks. The variance between thresholds for inviduals does not have to be significant, but is necessary for the increase of specialization in threshold models [23]. In some variations of this model, an agent's threshold for performing a task will decrease after it has performed that task. On the other hand, when the agent chooses not to perform a given task, the threshold for that task is increased. The specialization related to that task is thus reinforced [49] if performed. Empirical evidence in natural systems suggest that the threshold levels for the performance of tasks changes over the lifetimes of individuals [5, 42].

5.3.2 Social Inhibition

The social inhibition model is one that posits that as agents choose their specialization, they are able through interactions to notify other agents of this choice. In these interactions, they are also able to inhibit the desire of other agents to perform this task. The main aim of the model is to explain temporal polyethism in biological colonies. Temporal polyethism is age-based specialization, where the older agents are more likely to perform certain tasks than younger agents [5, 22?]. The initial form of this model was an activator-inhibitor approach, where agents would eventually mature to perform specific tasks, while the inhibitors they have received from interactions with others would slow their activation [14].

Naug and Gadagkar presented a formalized model based upon [22] that sought to explain age polyethism in wasp species [38]. In this model, agents possess a couple pods: one that is responsible for increasing the agent's preference for performing a task, and another that will inhibit interacting agents preferences for performing the same task. The authors claimed that individual levels of specialization emerged due to the increase in age-based activator, as well as the amount of inhibitor exchanged during agent interactions[38].

In the social inhibition model, the tasks chosen by agents is not directly determined by their interactions with others. In fact, agents are not themselves responsible for choosing their task. The model ranks tasks in a way related to age. Agents are sorted by activator level and then assigned to perform tasks. This requires the existence of central control for the model to work correctly [22, 38].

5.3.3 Weight-Allocated Social Pressure System (WASPS)

Cockburn and Kobti presented the a weight-allocated social pressure system (WASPS) for the emergence of agent specialization [14]. The model is a variation of the social inhibition model. Instead of age-based specialization, they aimed to create a competition driven social inhibition model. Their model had two primary assumptions: 1) agents could divide their resource (i.e. time) among each task 2) agents have varying levels of skill in the performance of each task.

In that model, agents would allocate a certain percentage of the resource to be divided among each available task. When an agent would interact with another, they would inhibit each other's desire to perform the task. In their model though, agents would also self-reinforce when they interacted. This allowed more efficient agents to increase the weight they allocate to a task if they interact with a less efficient competitor. They were able to show that the level of specialization within a population would increase due to the increased competition. An interesting observationw was also that agents would not necessarily specialize at the task that they are most skilled at. They would allocate resources more to tasks for which they have larger comparative advantages in relation to their competition. As we will be showing how the WASPS model can mimic existing models such as the genetic threshold model and the basic social inhibition model, we present the description of the model as found in [14] below.

5.4 Weight-based model for resource allocation among tasks

The following was presented in [14]. Our approach is not aimed at system optimization, whereby the system itself tries to be the most productive possible. Instead, agents should be able to emerge the specializations that they are most suited for in their given environment. We assume the existence of a set of tasks T. Each element *t* in T is a task that can be performed by an agent. Each agent has a level of skill associated with each task. The skill level may be static, or it may be determined by the agent's previous success at performing the task. This allows for skill levels that may correspond with fitness functions in evolutionary algorithms. This skill level is quantifiable, comparable and monotonic, such that $sk_a(t) > sk_b(t)$ means that agent *a* is more skilled than agent *b* at performing task *t*. All agents assume they can perform the task perfectly. The level of skill is then reflected in the amount of inhibition that agent then releases when they interact with others. Agents are thus able to determine their true relative skill level through interactions with other agents. The strength of inhibition, which we refer to as the influence rate, depends on each agent.

For each agent Ag, we propose a set ALLOC, where $e_i \in$ALLOC $\Rightarrow$there is a task We in T_{Ag} and e_i represents the weight allocated to task i. Task weights in ALLOC are relative, therefore for a given task We and a resource to be allocated R_{Ag}, the amount of R_{Ag} to be allocated to task We is: $\frac{e_i}{S(ALLOC)}$ x $S(R_{Ag})$, where S(ALLOC) is the sum of all elements in ALLOC. We make no assumptions about the initialization of the weights in ALLOC; they can be randomly assigned, or initialized by some other method. A task having a weight of 0 will result in the task being allocated none of R_{Ag}. For simplicity, we will assume R refers to time for the rest of this paper. We also normalize the weights in ALLOC such that S(ALLOC) is always equal to 1.

5.4.1 Model outline

Agents influence other agents when they interact. In some networks, such as kin network, it can be assumed that they interact with all their neighbours in each time step. The amount of influence is dependent on skill level. The higher the skill level, the higher the level of influence. When an agent interacts with another, it positively reinforces its own behaviour, while also inhibiting the other agent. The amount of self-reinforcement is the same amount that it inhibits the other agents. After all agents have interacted, the agent subtracts the level of inhibition it has received from the level of activation it has provided itself. The agent also self-activates itself, such that an agent that does not interact with any other agents will still change its behaviour. These effects result in the change of the allocation levels for the agent.

5.4.2 Agent Attributes

Each agent has the following attributes:

- An allocation set ALLOC = { ti <- [0,1]}, for all tasks We $\in$ T, where ti is the fraction of time the agent will spend on task i.
- A skill set SKILL = { si <- [0,1]}, for all tasks We $\in$ T, where si is the skill of the

agent at performing the task *i*. If an agent cannot perform a task *p*, then the value of *sp* would be 0. The skill level for a task may be dynamic and updated regularly. The skill value as a function must be monotonic though, such that if agent *Ag1* has *si* 0.5 and agent *Ag2* has *si* 0.7, then we can say that *Ag2* is better than *Ag1* at performing task *i*.

- A set PODS = { pi }, for all tasks We $\in$ T, where *pi* is a 3-tuple (A, SA, I). In this 3-tuple for task *i*, *A* represents the activator store for the agent, *SA* is the level of self-activation, and We is the inhibitor store for the agent. The agent will increase the weight of the associated task when $A+SA > 0$, and decrease it when $A+SA < 0$.

The idea behind self-activation is the inclination of an agent to perform more of the task at which they are best. This value should be large enough that it will allow an isolated agent to specialize over a long period of time, but it should also be small enough that it doesn't overwhelm the social pressure created by stronger competitors.

5.4.3 Agent Inhibition

The level of inhibition We in an agent's pod for a task We is determined by several factors:

- The skill level of the agent at performing task *i*.
- The size of the agent's social neighbourhood.
- The influence rate, $IR = (0, 1]$, which is a parameter that determines the strength of an agent's influence. This parameter can be universal, or variable for each agent. It is also possible that the influence rate can be different for each task. We can re-create the effect of polyethism if we were to make *IR* dependent upon the age of an agent.

5.4.4 Agent interaction

When agents *Ag1* and *Ag2* interact, for each task $t \in T$, we obtain the values in *Ag1*'s pod *pt* for task *t*, and *Ag2*'s pod *pt* for task *t*. The value in *Ag1*'s *A* will be decreased by *Ag2*'s We and vice versa. Each agent will also increase its own *A* by its *I*. This method allows agents to influence each other only when they interact.

Since agents both exchange inhibition, and inhibition level is tied to skill and influence level, the more skillful and influencial agent would have a greater effect on a neighbour than a less skillful and influential competitor. While the influence of the "better" agent would be stronger, the weaker agent would still inhibit the stronger one. It is also possible for agents to be considered to interact on every iteration, in which case agents would inhibit all others in their neighbourhood. It should be noted that the level of self-activation plays no role when agents interact.

5.4.5 Agent Attribute Updates

During each time period, agents will have performed their tasks based on their allocation weights (ALLOC). If the skill set is dynamic, then it would be updated based on the results of task performance. The influence rate of each agent would also need to be updated. If agents have different influence rates for each task, then the updates would need to be applied for each task.

Agents will then update their allocations based on each task pod. Given a normalized allocation *ti* for a task *i*, and a pod (a, s, x) for the same task *i*, then *ti* will be updated as:

$ti = ti + a + s$. That means that the amount of self-activator s will be added to the activator a, and the sum of that added to the current weight. If an agent was overall more skilled at a task than the other agents it interacted with, then its actiavator level a should increase. If it is less skilled overall, then the level should decrease, resulting in a negative value for a. After all task weights are updated for an agent, the values are again normalized, resulting in the sum of all weights in the agent's ALLOC being 1.

5.5 Hybrid Model

We have developed a hybrid model that uses features from both the genetic threshold model and the social inhibition model. Our model aims to address a problem that is not directly answered by either of these models; given agents with differing skills and an environment where task stimuli varies, how can the population of agents select tasks such that more skilled agents are more likely to perform a given task?

In the traditional genetic threshold model, all agents who have been activated (based on threshold) are qualified to perform a task. If these agents have different aptitudes for performing this task, then it is quite possible that less qualified agents will be selected to perform the task, resulting in less-efficient task performance. This isn't a problem in systems where all agents possess the same skill level for task performance, but it is our view that there are many systems where agents have heterogeneous skill levels.

To answer the problem, agents all possess a threshold at which they will be willing to select a task. Like in several genetic threshold models, agent thresholds will change in response to some factor [5]. In our model, there will be two drivers for the changing in agent thresholds. The first is an internal pull toward performing the task at which the agent is most skilled. The second is competition from other agents. The two factors are weighted equally in an agent's update.

The agent's genetic pull is determined by the following formula:

$1 - \sin(sk_a(t)) \times 90 \times MT$, where $sk_a(t)$ refers to the skill level the agent a has for task t, and MT refers to the maximum threshold all agents can possess for a task. This creates a natural pull whereby agent thresholds will be lower whenever their skill for that task is lower. This creates a genetic stable point for agents. It should be noted though that it is quite possible for an agent's skill level to change over time, whereby the stable point for the agent's genetic threshold should change. In this paper, we don't examine that possibility, instead working with a static level of skill.

As the above genetic threshold determination will not differentiate agents by skill. To deal with this, we also create a social inhibition factor to an agent's threshold update. The method for the social update works similarly to that of the WASPS model. Unlike the WASPS model, agents only perform one task at a time, which would make the ALLOC set superfluous. Thus, the ALLOC set is used to represent an agent's threshold for a task, as opposed to the fraction of a resource to spend on that task. The threshold values can range from 0 to MT. As the values in ALLOC are no longer relative to each other, we therefore no longer normalize the values. The SKILL and PODS attributes remain the same. The inhibition factors are simplified, only varying by agent skill levels. The influence rate (IR) is set at 0.5. The formula for the amount of inhibition agent a will give to another interacting agent is:

$sk_{\mathrm{a}}(t) \times IR \times MT$

Agent interaction is the similar to the WASPS model, with the additional limitation that agents only interact with other agents that performed the same task. If an agent did not select a task (because its threshold was not met), then that agent is considered to have not interacted with other agents. The activator update is also similar to WASPS, with the self-activator s being 0 (more on this later). The amount of inhibition exchanged between agents is deducted for the total amount of activator each agent possesses. We note agent that agents also increase their activator level when they interact with others. Thus, the level of activator will be positive if the agent was on average more efficient then its competition, and negative if less than the average.

For self-activation s use in WASPS, we now use the agent's genetic pull as outlined above for active agents, and a constant decrease for non-active agents. For non-active agents, their threshold for each task is decreased by a constant ad-hoc factor (we used 5%). This will allow inactive agents to reduce their thresholds until they are low enough for them to perform a task. This is no guarantee that these agents will remain active, because if they are less efficient than other agents performing the task, they will again have their thresholds increased due to the competition and the active update formula given. We should also note that an active agent with no competition will not update at all (an implicit assumption that it does not need to).

5.6 Experiments setup

We use a mutual information and Shannon entropy index [47] metric developed in [19] to measure the level of specialization within the agent population. On each iteration of a simulation, each agent records the task that it has chosen to perform. If the agent is inactive, then it does not record any task, meaning they are not counted in specialization statistics. The task record is stored in an *nxm* matrix, with *n* being the number of agents and *m* the number of tasks. This matrix is normalized, resulting in the sum of all cells being 1. We calculate the mutual information and Shannon entropy index for the distribution of individuals across tasks. We finally divide the mutual information score by the shannon entropy score, which provides a value between 0 and 1. The higher the value, the more specialized the population is. A score of 0 is therefore a population with no specialization, while a score of 1 is a fully specialized population [19].

We also developed our own metric to measure, which we call the Quality of Work (QOW). It is a measure of the average amount of skill used in performing a task. The quality of work is a value between 0 and 1. A higher value indicates that the task was performed by a more skilled agent. Considering that all our agents have an average skill level of 0.5, a random assignment to tasks would also provide a QOW score of approximately 0.5.

We compare our hybrid model with the standard genetic threshold model, with the added requirement that agents also possess a level of skill for each task. We use the WASPS model to mimic the genetic threshold model. To do that we perform the following operations:

1. Disable social network
2. Task thresholds are indicated in ALLOC set, with values between 0 and MT
3. Agents all possess a level of skill
4. Set influence rate to 0 (as there is no social network)
5. Increase self-adaptation level to 1 (so full adaptation)

(a) This will cause preference to be immediately effective

6. To perform only 1 task, agent chooses randomly among tasks that have surpassed threshold

The result of the above changes is that the WASPS model will completely emulate the genetic threshold model. Agents will perform one of the tasks that cross its threshold, or be inactive if no such task exists. For task stimuli changes, we follow the method similar to that used in [23].

Each time a task T_j is performed by an individual, the stimulus intensity S_j is decreased by an amount a (a=3, arbitrarily chosen and also followed in this paper). For each time step, the level of the stimulus S_j associated to task T_j is increased by β_j, where $\beta_j = \alpha \frac{N}{T} \delta$. N is the group size (number of individuals as we use a global network), T the tasks number, and δ the demand level, which was always 1 in our simulations [23]. On each iteration, an agent would choose randomly from each task which surpasses its threshold for that task, or be inactive for that iteration. Each simulation was ran for 1000 time steps, with the stimulus leve initially set to 0 and increasing at the beginning of each time step. Simulations were ran 100 times for each combination of parameters. Each individual was given a uniformly random initial threshold value for each task between 0 and 3, which served as our maximum threshold (MT). Each agent was also given a uniformly random skill level between 0 and 1 for each task.

For our hybrid model, the initial setup is the same as with the genetic threshold model. The primary difference is the threshold update performed at the end of each iteration. Simulations are ran for both methods initialized with the same population. This means that the same population is created, with the same skill levels and thresholds, then ran once using the genetic threshold model, then again using the hybrid model.

5.7 Results

The two models were compared across several combinations of task and agent counts. We tested with 2, 4, 10, and 20 tasks. While most studies only involve 2-5 tasks, we followed the numbers used in [14]. We also tested with 10, 50, 100, 500 and 1000 agents. For each combination, we measured the resulting level of division of labour (DOL), as well as the quality of work (QOW). The results are illustrated in figures 1 - 4. Each graph illustrates 4 items; these are the level of specialization under the genetic threshold model (gDOL), the quality of work under the genetic threshold model (gQOW), the level of specialization under the hybrid model (hDOL), and the quality of work under the hybrid model (hQOW). Each value is the average of the 100 runs for the combination of parameters. The y-axis of each graph presents the value between 0 and 1. The x-axis represents each level of agent count that we used.

The first thing we notice is that there is a general increase in the level of specialization as the agent count increases. This is in keeping with the findings of [23]. In all cases, the QOW with the genetic threshold model is approximately 0.5. This indicates that agents are no more likely to perform tasks they are more skilled at. In most cases, we also see the increase in specialization with population numbers in the hybrid model. We do see a dip in the level of specialization in our results with 20 tasks when comparing 10 agents and 50 agents. While in all cases we saw a lower level of specialization in the hybrid model, there were particularly low results with 10 agents and 10 tasks. This seemed to be consistent in all 100 of the runs that were put together to produce that average. We believe this has something to do with there being the same amount of tasks as agents, but this is something we'll have to further investigate.

Unlike the genetic model, we noticed significant increases above the average in terms of QOW. QOW under the hybrid model was higher than under the genetic model in all cases. We can thus claim that the hybrid model produces a higher quality of work, and allows agents to specialize more on tasks for which they have a higher aptitude (skill-based specialization). Similar to what happened with the genetic model, the level of QOW also increases as the agent count increases. Based on these results, we can confidently claim that the hybrid model presents a trade-off. It produces a lower level of overall specialization than the genetic threshold model, but produces a higher quality of work. It results in more skill-based specialization, which is something that is not addressed in the genetic threshold model.

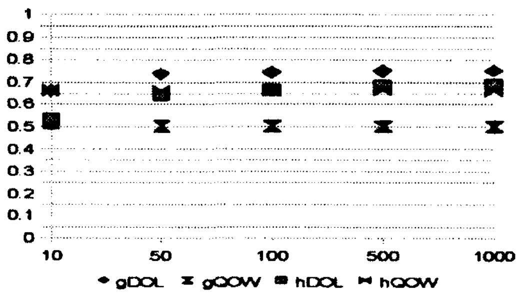

Figure 5.1: DOL and QOW with 2 tasks

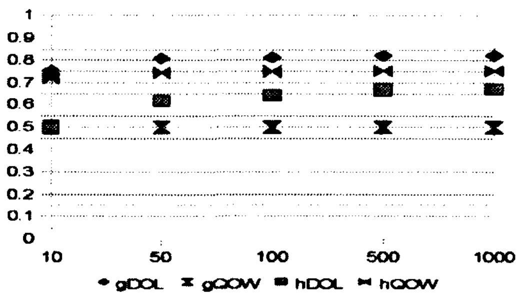

Figure 5.2: DOL and QOW with 4 tasks

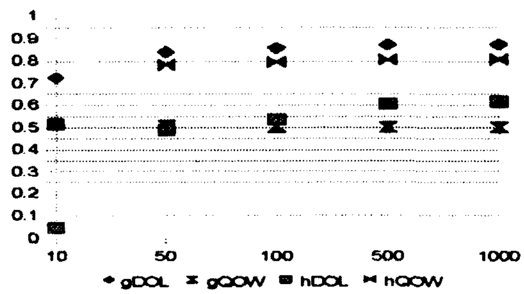

Figure 5.3: DOL and QOW with 10 tasks

Figure 5.4: DOL and QOW with 20 tasks

5.8 Conclusion and future work

In this paper we presented a model for the emergence of agent specialization when agents possess different aptitudes for tasks. This model is a hybrid of the genetic threshold model and the WASPS model. We saw that while this hybrid model led to an increase in the level of agent specialization, this level was lower than that seen in the pure genetic threshold model. On the other hand, the hybrid model did show increased skill-based specialization. It is our conclusion that there is a trade-off related to the hybrid model; a lower overall level of specialization, but a higher quality of work. This hybrid model allows for the study of specialization in populations of heterogeneous agents with different skills. In the future, we'd like to investigate other formulas for the social update of agent thresholds. We believe it may be possible to get even higher levels of specialization with other formulas that can better exploit differences in aptitudes between agents.

Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants*. Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 – 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f3705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

Chapter 6

A Social and Economic Model for Agent Specialization in the Simulation of Human Societies

6.1 Preface

This unit served as the most intensive test environment for the WASPS computational model. We implemented the WASPS model within the Village Eco-Dynamics Project (VEP) II, which is a large and complex research model. The goals were multiple, but primarily driven by anthropological concerns. The aim was to study the effect of specialization upon the study population. WASPS was a natural model for this setting, as agents within the study population would naturally divide their energy expenditures among multiple tasks. It was also the case that agents were not equally skilled at performing different tasks.

The environment within the VEP is very constrained. It has been developed over the last 20 years with input from many different academic fields. In addition to the environment constraints, WASPS needed to allow for agents to be able to survive mistakes in planning.

Due to the constraints given, WASPS had to be modified (while remaining true to the model itself), to allow the necessary behaviour. Note that we returned to using weights within this implementation.

The first interesting change was the determination of social influence. Agents would influence the behaviour of their neighbours only if they possessed amounts of resources in excess of what they need for the subsistence of their families. In a sense, this translates to only more successful agents possessing any social influence. Agents would only influence agents that are less efficient than they are (another way of looking at it is that agents ignore the advice of less successful agents). To avoid false influence, agents would divide the available level of influence equally among all weaker competitors. Based on trade range limitations, the neighbours that would be exposed to influence would be limited to a certain geographic range. Another social influence change was that agents would also ignore influence if it would put their family at risk; an agent would not be willing to reduce procurement of a resource if they already possessed less than they believe necessary to feed their family (the target threshold was 2 years supply of the resource).

Individually, agents would themselves try to adjust their weights to be able to procure enough resources to get back to their threshold. This would be combined with the changes called for by social influence. We also should note that agents were limited in how much they could change their allocations during an iteration. This was another safety restraint to prevent agents from dying too quickly because of planning mistakes.

The implementation of WASPS within this environment lead to many interesting conclusions. These are to be presented in a paper currently in progress. As to specialization itself, we were able to see increases in specialization levels when social influence was added to the system. WASPS has thus provided a framework within this complicated system to be able to study the effects of agent specialization in many future contexts. This was something not able to be produced with these constraints by existing models.

6.2 Introduction

Specialization allows agents to maximize their productivity [37] by cooperating with other individuals with whom they interact [48]. We define specialization as the choice to produce quantities of some goods in excess of a level needed for subsistence, while simultaneously underproducing other goods. When agents specialize, if they don't produce all their subsistence goods, then they must acquire these through trade with other agents [16]. Specialization can be viewed as a spectrum. Agents can be fully specialized, performing one task to the exclusion of all others, or they can be partially specialized, performing all tasks to varying degrees. In our system, our agents are expected to be partially specialized, but it is also possible for some agents to become fully specialized.

Specialization increases the productivity in a market system [37]. Productive individuals increase the supply for goods in which they specialize, and they specialize in producing goods in which they have a comparative advantage; at the same time they increase demand for other goods that they need [55]. The level of specialization and output are dependent on several factors, including competition, trade networks, and initial conditions [33].[?] created an economic agent specialization model that added features not found in [33], such as consumption, production limits, changing populations, and changing trading relationships. If many agents are already performing the same task and outputting the same resource, then the supply for that resource is likely to surpass the demand, resulting in it being illogical for more agents to supply the same resource.

It has also been shown that the level of specialization in complex systems, including human societies[6], is affected by the size of the system [8]. The behaviour of cognitive agents can be modeled using motivation networks [31] in which agents choose between moving, eating and breeding based on conditions within the environment. Our human agents are not specialized to this degree, and only use specialization to determine what jobs to perform (and how to divide time among those tasks).

[12] and [13] claimed that introducing social influence into a system would increase the level of specialization. We create a model that incorporates both economic state and

social influence. Agents are influenced by demand and competition from other agents in their topographically based social network. It is expected that there should result a higher level of task specialization in this socially-influenced system, than in the models without social influence. It is also expected that the level of wealth will increase in the population, based on [37]. We therefore compare the system whereby agents only try to procure enough resources to meet their needs, where agents plan based on the economic state of their family, and finally, where agents plan based on their economic state but also factoring demand and competition from agents within their social network.

6.2.1 Social specialization

There are several approaches to modeling social specialization, including social inhibition, whereby agents discourage others from competing [5]. Temporal polyethism is another, where agents' specialization change dependent upon age [43]. Agents can also learn from experience [37, 48, 49]. In this case agents may randomly select a certain specialization, and if they succeed, the probability increases that they will select that action next time.

For these reinforcement-based systems to succeed in dynamic environments, agents must be able to overcome previously learned behaviour, especially when failure to do so results in death [4]. Agents must be willing to engage in behaviour that previously had poor results and also must be able to respond to emergency situations, where change may be dramatic yet necessary. Moreover, the level of social influence within a society also affects the level of specialization. The more affected agents are by the actions of their neighbours, the more specialized the society becomes [12, 13].

Evidence suggests that the level of specialization within insect societies is positively related to the size of colonies, so [23]studied how group sizes and economic demand affect division of labour. Their results indicate that when demand is low and there are many tasks, increased division of labour is an emergent property [23].

6.2.2 Multi-agent systems

Not all study of specialization is primarily concerned with the individual. In Multi-Agent Systems (MAS), the study of specialization is motivated by an interest in how specialization can increase the efficiency of the system in reaching its goals. A Markov-chain model to describe the evolutionary dynamics of MAS is presented in [10]. In that environment, agents search for and exploit resources with incomplete information and a goal towards maximizing the efficiency of the entire system. The MAS uses a centralized model for determining task specialization, with the resultant task allocations emerging due to long-term system evolution. Thus, agents' specialization is determined by the overall needs of the system and not by individual considerations alone. As a result, an agent can sometimes be caused to specialize in tasks that are dangerous to its personal interests without sufficient reward (i.e. the job of cleaning up a toxic spill). Agent specialization in these systems will result in higher system productivity than in non-specialized systems [10].

Using a centralized specialization system also addresses another problem: agents generally do not possess complete information, thus any specialization decisions they make are likely to be suboptimal. Centralized MAS are better able to handle specialization in complex and changing environments [10], in part because complexity itself arises from the self-adaptive properties of individual agents [20]. These centralized systems benefit from the fact that resources discovered by individuals are then able to be more quickly exploited based on this global system knowledge and direction.

Centralized MAS, however, put the burden on the system to be fully aware of all relevant factors in the decision making process for all agents. There is no competition between agents in these systems. These systems also require the existence of colonies of cooperating agents, which means they are not applicable to systems of autonomous or even cognitive agents (as they would then be able to override the centralized decisions). They are also not realistic for our target system, which embraces a large number of autonomous communities in a large study area.

6.3 ApproachProblem Description

Given agent Ag, the set T_{Ag} and a resource R_{Ag}, how does an agent allocate its R_{Ag} among each task t in T_{Ag}?

So: $\Sigma x_i = S(R_{Ag})$, where i is each task in T_{Ag}, $S(R_{Ag})$ refers to the amount of the resource R_{Ag} available, and $x_i$refers to a fraction of $S(R_{Ag})$.

The problem also involves the following conditions:

The problem is continuous over a period of iterations

$S(R_{Ag})$ changes between iterations

x_i is allowed to change over iterations

Each agent Ag also has a set REQ_{Ag}, such that a resource r $\in$REQ $\Rightarrow$Ag needs some amount of r for subsistence between iterations.

6.3.1 Weight-based model for time allocation among tasks

For each agent Ag, we propose a set EC , where $e_i \in EC \Rightarrow$there is a task i in T_{Ag} and e_i represents the weight of task i.

Task weights in EC are relative, therefore for the given a task i and a resource to be allocated R_{Ag}, the amount of R_{Ag} to be allocated to task i is:

$\frac{e_i}{S(EC)}$ x $S(R_{Ag})$, where S(EC) is the sum of all elements in EC. We make no assumptions about the initialization of the weights in EC. They can be randomly assigned, or initialized by some other method. A task having a weight of 0 will result in the task being allocated none of R_{Ag}.

Ag must possess some evaluation function P(t) for each task t in EC. P(t) is assumed to be a composite function, assumed to be an economic performance function. P(t) is applied to each task in EC after the performance of that task, therefore representing the result of performing the task. If P(t) > 0, the task is assumed to have had a positive result, in which case e_t is increased by some factor, which is domain dependent. In the case of P(t) < 0, e_t is similarly decreased by some factor. The result of this process is the updating of the weights in EC, which in turn determine how each agent allocates the resource in question.

Our weight adjustment model is a reinforcement learning model, as household's learn and adjust based on previous experiences. Note also that agents are not concerned with the results or experiences of their neighbours

6.4 Case Study: Village Ecodynamics Project

The Village Ecodynamics Project (VEP) [30] is a multi-disciplinary project involving many institutions. It has involved individuals from Washington State University, Crow Canyon Archaeological Center, Wayne State University, and University of Windsor, the Colorado School of Mines, University of Notre Dame, and BBL, Inc. Researchers include computer scientists, archaeologists, ecologists, anthropologists, geologists and economists. We are describing and modeling 1800 km^2 of the central Mesa Verde region of Southwest Colorado, occupied between A.D. 600 and 1300 by farmers ancestral to contemporary Pueblo peoples . Thousands of habitation sites are known from this area, which we can assign to one or more of 14 periods based either on excavation or, in most cases, the ceramics on their surfaces [52]. The entire northern Southwest was depopulated towards the end of the thirteenth century and one of the primary goals of the research is to understand reasons that led to this depopulation [30].

Another goal of the project is to understand why, during certain times in prehistory, most people lived in large and relatively compact villages, while at other times, they dispersed into smaller hamlets. Much of the dynamism of the simulation is provided by annual and spatially specxific estimates of potential maize production on this landscape, originally developed by Carla Van West [51]. The simulation was designed by Tim Kohler [29] and colleagues at Washington State University and the Santa Fe Institute.

The model creates agent households that live, work, and reproduce in a simulation based on the data collected on the region. Agents are responsible for gathering their resources, while feeding their families and trading with other agents. Agents can farm maize, hunt (cottontail, jackrabbit, and mule deer) for protein, obtain water from rivers andsprings, , and also gather wood for fuel from forests. Agents get all their energy (calories) from maize. When protein is required, it costs calories to procure. Agent (households) must provide their families with enough calories to perform these tasks, as well as provide for their basic metabolic needs. In the case that the agent cannot obtain all their needed resources on their own, they are allowed to trade with other agents. Families are kept track of, resulting in different trade relationships between kin and non-kin agents. If an agent is not performing well at their present location, they will move to more suitable locations in the study area. Unfortunately for the agents, they are not allowed to exit the study area. When evaluating locations to move to, agents evaluate the resource productivity of the area to which they are thinking of moving. They evaluate the area for farming productivity, water accessibility and forestry and presence. The model aims to model soil productivity, rainfall, animal density, forest density, and other features of the region with a fair degree of realism. Even the vegetation in the simulation that feeds the animals is affected by climate variability.

The VEP area researchers have identified two population cycles in the archaelogical record [30]. The earlier, smaller one presents relatively little evidence for specialization, whereas in the later, more populous cycle there is evidence for specialization in the domains of political leadership, and probably also in provision of religious services and in aspects of ceramic production. Scott Ortman provides evidence that households relocating to the largest site in the VEP area, Yellow Jacket Pueblo, towards the end of its occupation, specialized in ceramic production, possibly because, as late arrivals, they did not have access to high-quality farm land [41]. The framework we create here will allow for the emergence of specialists within the simulation. Ceramic production for instance can later be added to the simulation.

A monograph with a great deal of additional information about the archaeological record, the structure of the simulation, and our conclusions derived from comparing the two, is currently under review. Also notable in the present context are the efforts by Kobti et al in investigating the role of exchange in aggregation and depopulation, using cultural algorithms [26, 27].

6.5 Simulated environment

The VEP environment consists of 4 resources: water, wood, maize and meat; all but wood are needed for survival. While an agent dies immediately if they do not have enough water or maize, depending on how parameters are set in the model they may need to be short of protein for 3 consecutive years before dying of malnutrition. Agents are allowed to survive continual shortages of wood (the agents don't factor this into their planning though). While agents are bound by these resources, they don't have any real understanding of their requirements for these resources. This means that an agent does not prioritize water or maize over wood or protein, even though neglecting the former increases the chances of death.

Each resource is associated with a task that produces that resource. A farmer produces maize, a hunter acquires protein, a woodsman gathers wood, and a water carrier retrieves water. Each task also has constraints and requirements for the performance of that task. Farmers require land to plant their maize. There are a limited number of productive plots on the landscape and plots vary in productivity, both within a year (spatially) and from year to year. Hunting requires the presence of animals within hunting range (a parameter set in the simulation). Gathering wood requires the presence of deadwood or trees, and carrying water requires that there are water sources that the agent can travel to. For wood and water, agents are not bound by the distance to these resources; they can travel as far as they need to in order to obtain them. All tasks require energy to perform, and thus require the agent to have enough calories to perform the task. The amount of energy required was part of the simulation before the development described here began, and is explained in [30].

Agents must allocate their family's total calories available for the year among the given tasks. The number of calories required by each household is determined by the number of adults in the household, the number of children in the household, as well as how many hours per day each is required (or willing) to work. In the version of the simulation reported here, the number of hours willing to work was set to 6 hours/day for every family. Agents are able to spend any amount of their calories on any specific task. While not measured, agents also have a secondary goal, the accumulation (storage) of resources that increases their economic security for times when they cannot procure additional resources, such as during a famine or drought. All agents can only store a maximum of 10 years supply of any resource. Any excess amount will be donated to nearby relatives, or discarded if there are no relatives to accept them. While agents must sustain needs to survive, their focus is on maximizing their productivity given their abilities. All agents have the same skill level, so ability is delineated by the productivity of an agent at performing a task. Thus an agent having more productive plots would get a higher return on the energy expended on those plots, and thus can be claimed to be a "better" farmer than an agent with less productive plots. To prevent agents from dying before they have time to procure resources, all households are given an initial allocation of two year's supply of maize and meat, as these resources can only be gathered in autumn and summer respectively.

It is not feasible to initialize an agent's allocation among tasks randomly . since a low allocation for farming may result in starvation, with similar unfortunate results for other resources. Additionally, the only way for a new agent to be introduced to the system is for a household to survive long enough to produce offspring. To address this problem, we have households calculate how much of each resource they need and allocate enough time to meet these needs. This only happens in the first year of a household being created. We use the resulting allocation of time in that first year to seed our weights for the second year. If an agent spends 25% of their energy in the first year farming, then farming will have a 25% weight in our system during the second year. After this, agents rely on a performance and feedback function to update their weights for subsequent years. Agents may not be able to provide themselves with all the subsistence goods they need, and thus rely on trading and begging to obtain those resources.

The simulation was modified with the ability of agents to pass on their wealth. If an agent household dies, the resources it has stored will be divided equally among its children who are within close range. If no children are within range, then its divided among neighbours, and finally, if no other agents are within range, the resources go to waste. This allows us to keep track of the productivity of the society over time.

There are many other processes that agents perform that are outside of this work. New births and age-related deaths are examples of this. We also acknowledge that some of the changes we've made to our simulation are not realistic for the target context. One such example is that agents in our simulation can store infinite amounts of a resource, such as water. At this point we are striving less for historical accuracythan to create a framework within which domain experts may implement historically accurate constraints.

6.5.1 Agent steps

Below are the general decision-making steps required of each agent.

1. If first year in current location, perform based on family needs
2. If second year in current location, use allocations from previous year to initialize weights
3. Perform tasks and expend energy (eating, performing those tasks)
4. Exchange resources if needed
5. If still alive, update weights (defined in section 4.5)
6. If agent location is not sustainable, then move to new location.
7. Goto 1

6.5.2 Agent states

Agents have 4 states for each resource as it relates to health and trading. Calculations for each state depends on the size and makeup of each family. The calculations do not include usage of the resources for the purposes of working or performing other tasks. The states are based on how long the agents estimate the amount of the resource they possess will be able to meet their family's needs.

- TRADING - 2 years supply or more.
- SATISFIED - 6 months to 2 years supply
- CRITICAL - less than 6 months supply (but above 0)
- STARVING - When an agent doesn't have any of the resource needed, and needs to immediately obtain some via trading or begging.

6.5.3 Exchange

6.5.3.1 Barter Exchange

Barter, which is new to this version of the simulation, allows agents to trade one or more resources in exchange for another resource. We use a simplified barter exchange system in which agents trade goods based on a fair valuation system. Prices are therefore not negotiated between agents. To determine values for resources, we use the agent's cost of production. We accept that this does not result in the level of inequality that one would expect in barter system where prices are negotiated. For instance, in such a system, we'd expect that if an agent has the sole supply of a desired resource, this would inflate the price of that resource much higher than the agent's cost of production. We did not include such a mechanism as it would increase the computational complexity of the system beyond what we are currently willing to tolerate. While we do use calories as a form of currency in this simulation, we consider it to be infeasible to implement an auction system for resource pricing at this time.

If an agent (rAG) is in a state of CRITICAL or STARVING for a resource, it tries to obtain enough of that resource to get back to a SATISFIED state. First it must identify agents that it can possibly trade with for the resource. It does so by the following process:

1. Ask each agent tAG within trade range if they are willing to trade the needed resource and what they are willing to accept in exchange.
2. Call the set of resources that tAG is willing to accept RWA(tAG)
3. If tAG has enough of the resource being requested by rAG (tAG is in a TRADING state for that resource)
   (a) If rAG has enough of one of the resources being demanded (in a SATISFIED state or better) by tAG, then add tAG to a list of trade partners, which we can call TList.
4. Sort TList in order of price for the resource being sought.

After finding out which agents within its trade range are potential trade partners, rAG must then ask these agents to trade in exchange for what it can offer them. That process is as follows:

1. For each agent tAG in TList
   (a) Calculate how much of the required resource tAG is willing to sell. tAG is willing to sell any amount as long as it would not fall below the TRADING state.
   (b) Filter RWA(tAG), removing resources where rAG is not above the CRITICAL threshold for that resource. The resulting set can be called TRADE_SET.
   (c) Calculate how much of the required resource tAG is willing to offer (so that it doesn't fall below TRADING), we can call this set OFFER
   (d) Limit OFFER to the amount desired by rAG
   (e) Calculate an amount for each resource in TRADE_SET that is equivalent in value to OFFER. rAG is not allowed to fall below SATISFIED for any or these resources.

(f) If we can find a combination of such resources, then trade that combination of resources with tAG in exchange for the required resource.

(g) If we cannot find such a combination, then calculate the maximum total value of resources that we are willing to trade with tAG.

   i. Calculate the amount of the required resource that tAG is willing to give for that value.

   ii. Trade the selected amount of resources in exchange for the equivalent amount of the required resource that tAG is willing to give.

(h) If rAG is now in a SATISFIED state for the resource, then stop, otherwise move to the next agent tAG in TList

As stated above, the value of a resource is determined by the cost to the agent to acquire that resource. So if it costs an agent 1000 calories to acquire 10 kg of protein, then the value of that protein is 100 calories/kg. Agents do not question the value of resources as determined by other agents. Note also that agents are able to sort through those providing resources. This means that an agent knows who in their neighbourhood can provide the resource at the cheapest prices. This factor results in the requesting agent having an advantage in trade relationships, as it can sort selling agents by price, but selling agents will accept the cost to rAG to produce the goods being given in exchange.

6.5.3.2 Generalized Reciprocal Exchange

Agents keep track of their kin. An agent household (husband and wife) will know the households of its parents (the male and female's parents), as well as those of its siblings (again, on both sides). This leads to the introduction of the generalized reciprocal network (GRN) [26, 27]. This network operates over the kinship network between households. In GRN, agents are able to make requests for resources from members of their immediate family. This provides a social safety net whereby families band together to help each other survive. Agents are not expected to repay resources that they obtain in the GRN. So if an agent obtains some maize from a parent, they are not expected to repay that gift. This works out in the long run for agents because if that parent later were to ask the child for help, the child would be alive and willing to help. We do not go over the internal logic of the GRN, as this can be found in the papers listed above. In addition to requests, agents in the GRN in a TRADING state will donate some of their resources to a member of their family. All trading and donation in GRN are limited to a certain geographical distance, which is a parameter set in the simulation. Kin will not put themselves below the SATISFIED state to help, as this may put their own household at risk. GRN is currently only implemented for food resources such as maize and protein.

6.5.3.3 Balanced Reciprocal Exchange

The balanced reciprocal network (BRN) is a reputation-based borrowing/loaning network. Agents are willing to loan resources to non-kin neighbours within a specifiable trading range. This is based on a probability system (another parameter), so agents will not automatically loan to someone requesting, even if they have a good or neutral reputation. If an agent loans a resource to a neighbour, they expect to receive that resource back when they ask for it. If the neighbour repays when asked, then their reputation remains intact. If the neighbour is unable to repay the loan, this will damage their reputation. Reputations are only dyadic (between two agents), so it's possible that an agent may have a really bad reputation with one agent while having a superb one with another.

Agents are able to improve their reputation by loaning resources. If a neighbour loans an agent a resource, their reputation with that agent goes up. This means that later if this neighbour is in need of another resource that the agent is able to provide, they will more likely do so. Resource transaction in the BRN is like-for-like. This means that if an agent is loaned some maize, they are expected to repay in maize. They cannot repay any equivalent debt in a different resource such as protein. Like GRN, BRN is only implemented for food resources such as maize and protein.

Neighbours are much less generous than kin. A neighbour agent has to be in a TRADING state before they are even willing to consider giving. After this they are then willing to consider the reputation of the asking agent. The asking agent needs a positive or neutral reputation before the neighbour will proceed. After these two requirements, the neighbour will consider whether they are in a loaning mood (the previously mentioned probability). Note also that a neighbour will not allow itself to fall below a TRADING state in loaning a resource to an agent.

BRN is based on neighbour exchange. It promotes a strong community bond between agents. While agents do not account for this, larger communities provide more opportunities for trade and assistance. Of course this would have to be balanced with competition for resources, as if a community gets too big, resources may become scarce. This potentially would result in agents having to leave their community to find a more productive location, even at the cost of losing their current trade network partners.

6.5.3.4 Trading process

Agents first seek to obtain the needed amount of a resource via the barter network. If the agent still has not obtained enough of the resource it needs from its trading partners and it's in a STARVING state, it attempts to use one of the other trading networks. First the agent uses the GRN trading network to ask up to 4 kin (this is another parameter set in the simulation) to give it the amount it's short. If they cannot obtain enough via this method, they then try to borrow using the balanced reciprocal network. If an agent is still unable to meet their resource requirements, they then proceed to try to borrow the resource on the BRN. If after all this, rAG has still not been able to get the required resource, then rAG dies if the resource is mandatory (water, maize) or suffers malnutrition (protein), which may also lead to death after 3 years. Note again that the balanced and reciprocal networks are limited to protein and maize exchanges only. This means that an agent can only obtain water and wood via barter or by procuring them on their own.

6.5.4 Social Influence

By social influence we mean that an agent's choice of specialization is influenced by the choices of those within its social network. Given a choice between multiple specializations, we factor in what the agent's neighbours are doing and allow that to influence the agent's decision. An agent N is defined as a neighbour of an agent A if N and A are directly connected within the social network. It has been shown that in the majority of cases, social influence causes an increase in the level of agent specialization when compared to systems with no social influence [12]. [13] showed that the level of specialization within a system would increase as the level of social pressure increased. [14] showed that a weight-allocated social pressure system would be capable of emerging a high level of agent-specialization within a population. We build our current model by following that method.

Waibel and his team in [53] also used the concept of social influence, but with what essentially were fully-connected networks (where all agents are connected to all others). In that study, agents chose their specialization based on the result of a function that weighs both their genetic threshold levels and inverse social influence. Therefore, the chance of an agent choosing a task would be reduced when more agents are already performing that task.

For each agent Ag, there should exist a composite function Soc(t) for each task t in EC. Soc(t) would be a function representing the social influence towards performing task t. An example of such a function would be peer pressure towards performing a task. In an economic network, the social influence may be a reflection of the demand for a product. In such a situation, it is also possible to create the social influence function such that there also exists negative influence. An example of this would be negative influence in the case of a potential sale that's lost because a competitor could provide a better product. The handling of the result of Soc(t) is dependent upon the agent and the domain. Given the same example of an agent selling a product and the same demand influence function, an agent may reduce production or reduce the price of their product.

For our case study, we first designate r(t) as the resource produced by task t. Each agent requesting a resource r(t) exerts production pressure on its possible trade partners in the following manner:

1. Locate all agents within trade range, placing them in a list we call POSS
2. Determine an influence rate IR = 1 / the size of POSS
3. Let rAmount = amount of resource r(t) that Ag is seeking to procure
4. For agent tAG in POSS
   (a) exert upward production pressure on tAG for task t in the amount of rAmount x IR (For tAG: Soc(t) = Soc(t) + rAmount x IR)
   (b) Let tAmount = amount of resource r(t) that tAG has available, OR rAmount, whichever is lower
   (c) exert downward production pressure on tAG for task t in the amount of 2 x tAmount * IR (For tAG: Soc(t) = Soc(t) + amountTraded x IR)
   (d) If tAG and Ag completed a trade for r(t)
      i. Then amountTraded = the amount of r(t) traded between Ag and tAG
      ii. Exert upward production pressure on tAG for task t in the amount of amountTraded * IR (For tAG: Soc(t) = Soc(t) + amountTraded x IR)

4a: Indicates to each agent that may provide the resource that this agent has a demand for the resource.
4c: This pressure accords with an agent's expectation of completing a trade for the amount possible (tAmount). If the agent completes the trade, the pressure will be reversed based on the amount of resource traded. If the agent is unable to sell, then this is either because there exists another agent that was a better trade partner for the requesting agent, or the requesting agent did not have the resources that the selling agent was demanding in exchange for the resource.
4dii: This rewards the expectation of sale. The net effect is that if an agent is asked for

a resource and is able to provide it, then that means their current level of production is sufficient to meet demand.

A selling agent Ag, having excess resources available at the end of a production period (in a TRADING state) also exerts pressure on their competitors in the following manner:

1. Locate all agents within trade range, placing them in a list we call POSS
2. Determine an influence rate IR = 1 / the size of POSS
3. Let rAmount = amount of resource r(t) that Ag has that they were still willing to trade
4. For agent tAG in POSS
   (a) If production cost of r(t) is higher for tAG than for Ag
      i. Exert downward production pressure on tAG in the amount of rAmount x IR
      ii. Stated differently: Soc(t) = Soc(t) - rAmount x IR for tAG

Therefore an agent will attempt to indicate to competitors with higher production costs that it is a better source of the resource and that it would be more capable of providing that resource to them. This deals with agents who are within range of each other, but are both self-sufficient with regards to a resource. Exerting competitive pressure encourages the less efficient agents to lower their production and rely on the more efficient ones for the resource.

An agent that is pressured socially does not have to change its behaviour. If an agent is already in a TRADING state for a resource, they will ignore pressure to increase production. The reason is that the agent determines that it already had some of the resource that it could trade, but no one was able to buy it. The reason may be that no agent has anything to offer that the agent is willing to accept. In that case, increasing production will not lead to an increase in trade. Agents also ignore to decrease production if they are below a SATISFIED state for a resource. The reasoning for this is that the agent determines that the reason it was not able to procure more of the resource is because it did not have anything to trade the selling agents. Therefore reducing their production will not result in them obtaining more of the good and therefore antithetical to their survival.

6.5.5 Update function

We use a uniform update function for each task in our weight system. This update function is applied at the end of each year, and determines how the agent will allocate time for the upcoming year. Given task t that provides resource r and x amount of resource r:

1) If the agent is in a TRADING state, then assume y = x - the threshold for TRADING. The agent will then reduce the weight of task t proportionally that it should result in the agent producing y less of r than it produced this year. In other words, if the agent has 200 kg too much maize, then it will reduce the weight it applies to farming so that the agent expects to produce 200 kg less maize next year. To avoid an agent making too drastic a cut, based perhaps on an abnormal amount of a resource because of trading, we restrict the amount an agent is allowed to reduce a weight to 50% of the current value.

2) If an agent is in a CRITICAL or STARVING state, then the agent will attempt to increase the weight for the task t so that it expects to produce enough additional resources in the following year to get it to a SATISFIED state. Again, to avoid overcompensating, we restrict the maximum increase to 300%.

3) Apply any social pressure as determined previously.

6.6 Results

To evaluate our method, we run the simulation three times, once with agents allocating effort based only on family needs, which is similar to the original simulation, but with new additions such as the barter network and resource inheritance. We then run the simulation with agents allocating based only on their current economic state. In that case, agents set their weights for tasks based on the amount of a resource they have remaining. If they have more than they need based on their reserve threshold (TRADING state), then they reduce production. They increase production if they are below this level. The calculation for this update was explained previously.We finally run the simulation with both economic state considerations and social influence enabled. With the addition of social influence, agents will reduce their production of a resource if they already have enough, and there is another agent that can provide the resource at a cheaper rate than the agent's cost of production. Also, when agents are short of a resource, they will inform more efficient agents of their demand for the resource, while also increasing their own production. This was also explained previously.

We compare the different methods using several measures. One such measure is the level of task specialization, which is applicable only to the economic and economic+social comparisons. We also compare the proportion of population in each settlement type, which would show the sizes of communities that emerges as a result of adding specialization. We also note the change in the level of trade when agents allocate based only on needs, and when they attempt to specialize. Finally, we measure the accumulated wealth of the population when using the three methods.

To measure the level of task specialization, we use a method developed in [19]. The method calculates and quantifies the level of task specialization within a system. We use the weight given to each task to calculate the level of task specialization at the end of each step in the simulation. The weights of all agents are then stored in an nxm matrix, where n is the number of agents and m is the number of tasks. Therefore each row in the matrix represents an agent's time allocation among all tasks. The matrix is then normalized such that the total of all values in the matrix is 1. The mutual information and Shannon entropy index [47] is then calculated for the distribution of agents across tasks. The Shannon entropy is then divided by the mutual information score, resulting in a value between 0 and 1. A value of 1 indicates that all agents spend all their time on 1 task, which does not mean the same task for each agent. A score of 0 means that there is no task specialization, as would be the case when each agent divides its time equally among tasks. A full explanation of the details of the methodology is beyond the scope of this paper and can be found in [19].

We found that the level of task specialization within the system increased significantly due to the addition of social influence to the factors that agents consider. This further confirms the findings of [12, 13]. We illustrate the level of task specialization during each run in 6.4 and 6.5. In all figures, note that time is in years, with year 0 corresponding to AD 600 and year 700 corresponding to AD 1300.

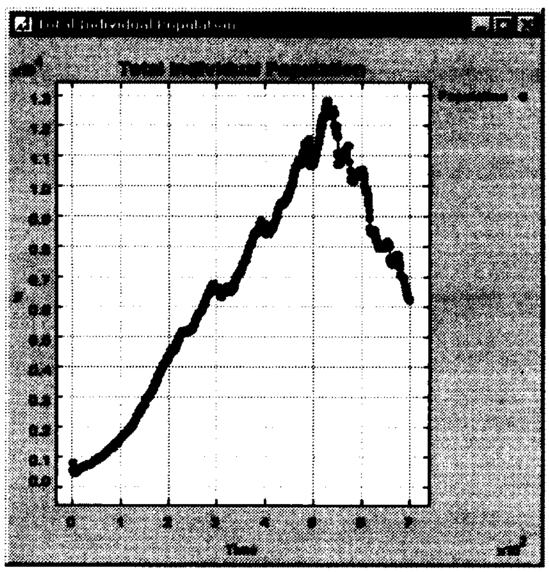

Figure 6.1: Population when allocation solely based on needs.

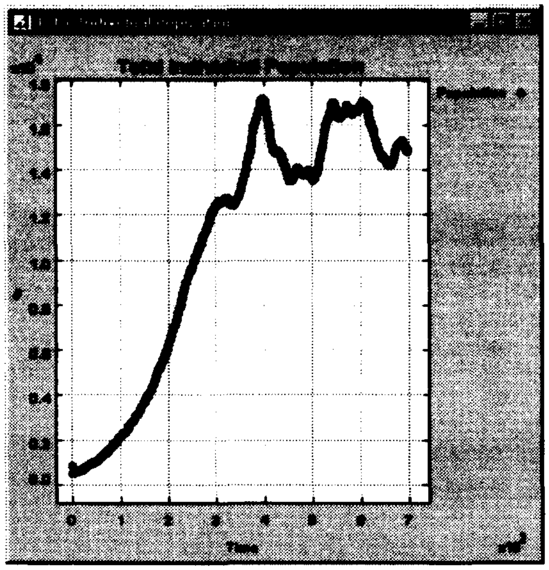

Figure 6.2: Population when allocation based only on economic state.

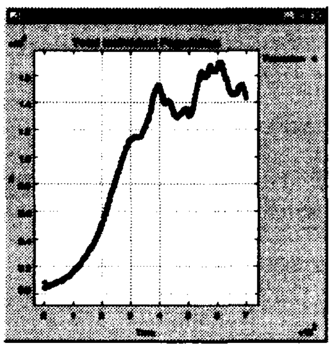

Figure 6.3: Population when allocation based on economic state and social influence.

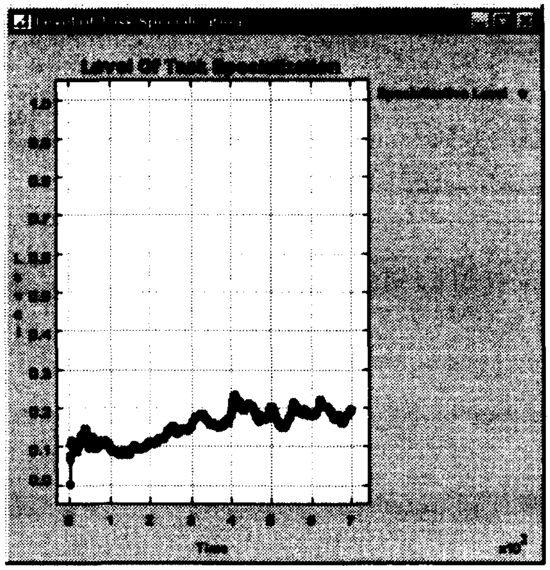

Figure 6.4: Level of task specialization when allocation based only on economic state.

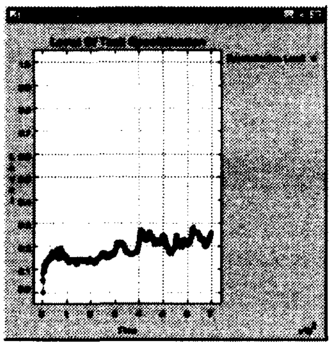

Figure 6.5: Level of task specialization when allocation based on economic state and social influence.

As previously stated, agents will move if they are not thriving at their current location. When choosing a destination, these agents do not factor in the presence of other agents, or trade networks that may exist as a result of those individuals. Our results show that agents are more communal when they factor in economic and/or social factors. Without specialization, agents primarily live in small hamlets of 1-2 households, and few in community centers (of 9 or more households), as shown in 6.6. We found that even with just economic state influencing planning, agents live in big hamlets (3-8 households), this time surpassing the number living in smaller hamlets, which we show in 6.7. The proportion of agents living in community centers also increases. This suggests that agents move less as a result of adding specialization. The results also would suggest that an increase in agent specialization also leads to increases in community sizes.

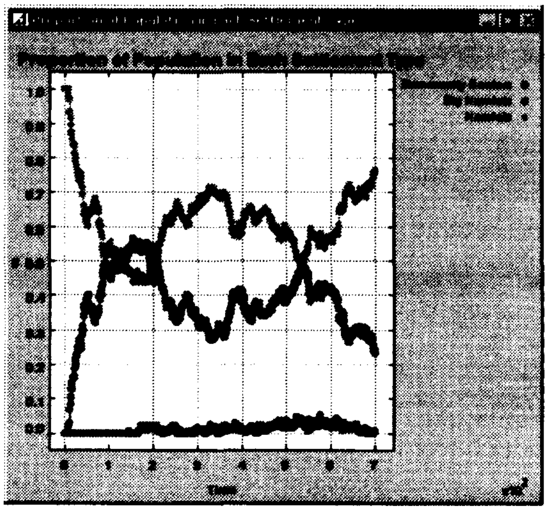

Figure 6.6: Proportion of households in each settlement type when allocating only based on needs.

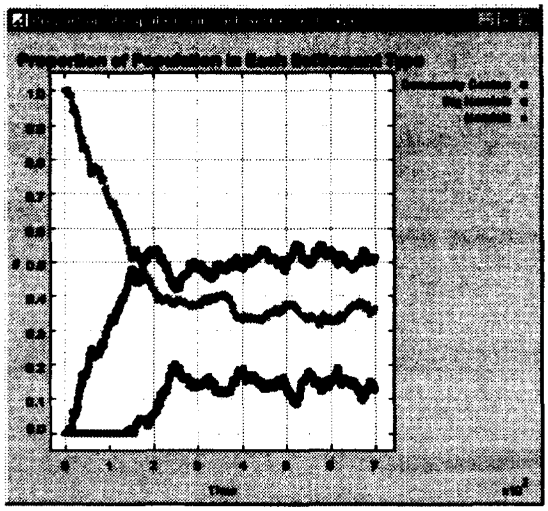

Figure 6.7: Proportion of households in each settlement type when allocating based only on economic state.

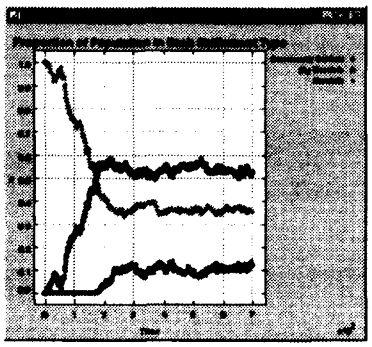

Figure 6.8: Proportion of households in each settlement type when allocating based on economic state and social influence.

Along with an increase in the proportion of households living in larger communities, we observed a significant increase in trade. This is due in part to workers working more hours on average, and thus trying to produce more than they need to meet their family's needs. The excess supply of resources results in more agents in shortage being able to find someone willing to meet that demand. We see in 6.9 that there is very little trading in some resources such as wood. With agents just trying to get enough for their own family, it's a lot less likely that they'll overproduce, which would leave enough for them to trade. We can also see in the same illustration that there still is a high level of demand for wood. Those agents that need the resource would not be able to get it supplied. With the change in allocation strategy, where issues such as demand is factored in, we can see that a lot of the demand for such resources can be met because there is more overproduction of resources. As seen in 6.10, the level of demand is not fully met, but is a vast improvement over allocating based only on family needs.

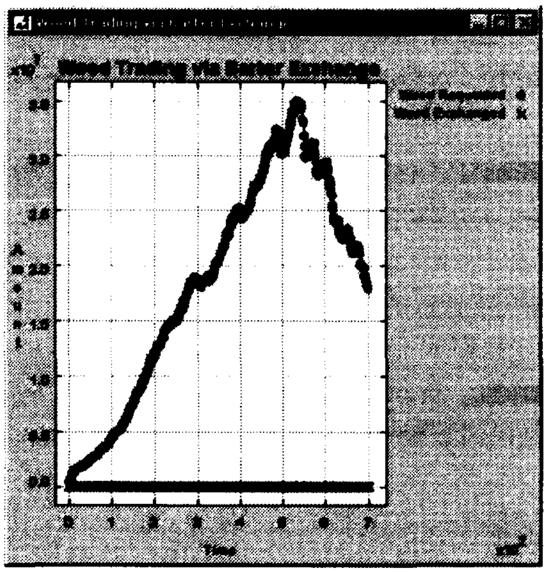

Figure 6.9: Wood trading when all agents are only allocating based on needs.

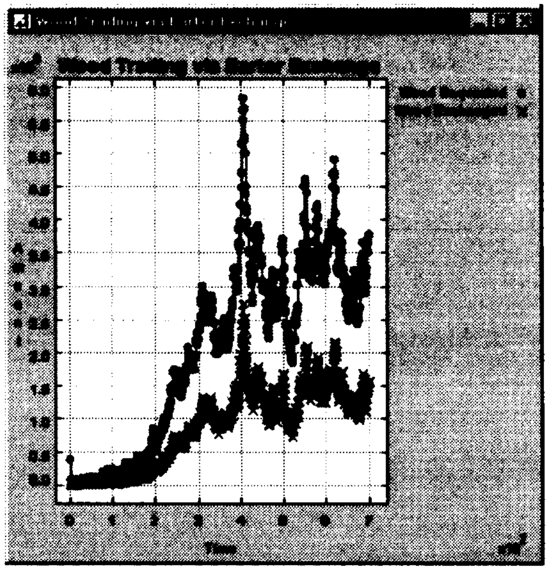

Figure 6.10: Wood trading when agents are allocating based on economic.

Note though that resources such as meat and maize decay over time, at a rate of 25% per annum and 10% per annum respectively. When agents are allocating their labor based only on needs, we found that they only had a few years supply of resources such as maize and water stored, as seen in 6.11. This would make sense as agents are only procuring what they need, and rarely overproducing. Overproduction reflects that the agent was not able to accurately estimate the needs of its family, or was not able to procure exactly how much it required. An example would be only needing half the protein that a deer posseses, but its not possible to only kill half the deer. On the other hand, when allocating based on economic and social factors, agents are much more productive. The resources they overproduce are maintained in the system (the society), resulting in higher average agent wealth, as illustrated in 6.13. We can see that there is still a low storage amount for meat. This is due in part to the high decay rate, as well as the depression of the most important meat source, deer.

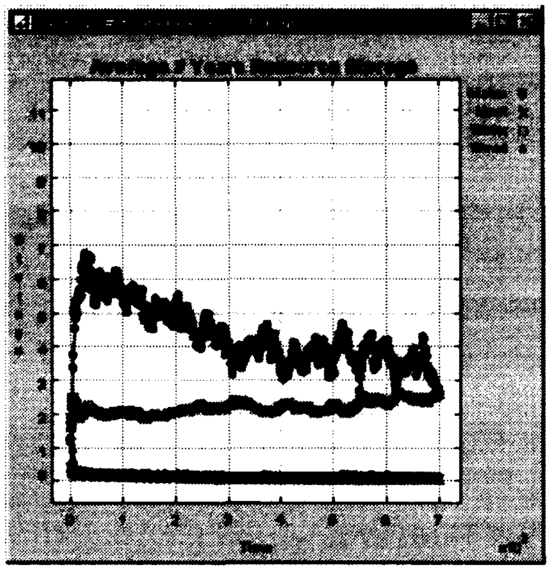

Figure 6.11: Average resource storage per household when allocating based only on needs.

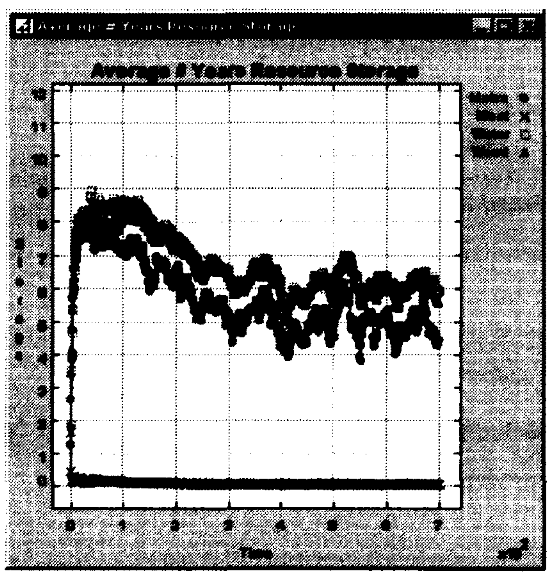

Figure 6.12: Average resource storage per household when allocating based only on economic state.

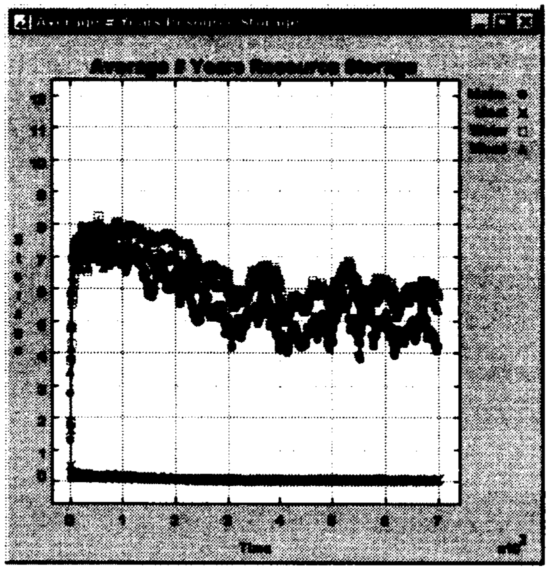

Figure 6.13: Average resource storage per household when allocating based on economic state and social influence.

6.7 Conclusion

In this paper we created a weight-based system for agent time allocation. This model allows different levels of specialization to emerge. Agents are allowed to determine the level of specialization based on their economic state as well as social influence from their neighbours. We tested this approach by implementing it within the Village Ecodynamics Project simulation as a case study. We found that as expected households became more specialized. Agents also began living in larger groups, and trading more with each other. The increase in productivity within the population resulted in an increase in the average wealth of the society over time.

Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants.* Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 – 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f3705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

Chapter 7

Conclusion and future work

7.0.1 Conclusions

In this dissertation, We presented the Weight-Allocated Social Pressure System (WASPS). WASPS is a computational framework that when applied, can allow for the increase in agent specialization within a multi-agent population. As specialization can lead to an overall increase in the productivity levels within a population [55], WASPS can also serve as a method of pareto optimization, even though we do not make that claim within this work. WASPS aims to provide a mix of features from existing frameworks. It provides individual level behaviour as found in the genetic threshold model. As in some variations of the genetic threshold model [49], WASPS also allows for individual level learning. As found in the social inhition models, WASPS allows for social influence, or population level learning. Unlike some models, WASPS allows agents to self-organize based on available tasks. In addition, it makes allowances for agents to allocate a resource among multiple tasks during a work period, wherein most models allow the selection of only one task.

WASPS allows the assumption that agents are heterogeneous in their task performance aptitudes. It thus aims to create skill-based agent specialization within the population. This will allow more skilled agents to allocate more resources to tasks for which they have comparative advantages over their competition. Because WASPS is self-organizing, it can handle the addition and removal of agents from social networks, as well as changes in the connections between agents. WASPS does not limit the definition of many or its parameters, which allows it to deal with changing definitions for those parameters. For example, WASPS can easily adjust to deal with changing definitions of agent skill and influence. In fact, the individual level learning can be implemented in such a way that an agent can self-optimize even when it has no competitors to influence it.

Because of the flexibility of the WASPS computational model, we are able to mimic existing models using WASPS. We showed in this dissertation the mimicry of the standard genetic threshold model. While not presented here, we also can mimic the standard social inhibition model and variations of both. It is my belief that WASPS is a better computational model than the social inhition model, primarily because it is self-organizing.

I also presented a case study where the WASPS was applied in the context of a Anthropological Multi-Agent System. We used the Village Ecodynamics Project (VEP), which is an extremely complex simulation of a society of Pueblo peoples during the years 600 - 1300 AD. The code base for the simulation is well over 20,000 lines of code, on top of the Repast Framework on which it is built [39]. VEP has been developed over the last 20 years, and with well over 50 researchers working on it over the years, with more than 30 currently working on it. Agents represent households that try to survive on a difficult landscape, where they must farm, hunt, collect water and wood. Using WASPS, we were able to provide agents with ways to increase their productivity, while also implementing the model in such a way that agents would have time to adapt to sometimes drastic changes in population and environment. For example, there are droughts and famines that happen during the simulation, when agents must have stored enough provisions to make it through. Through this all (much more than even can be explained here), we observed the desired emergence of agent specialization. The population reached a significant level of specialization, and maintained this level throughout, even as the population, environment, social networks and other things all changed underneath the computational model. This we believe, is a significant demonstration of the resilience of the WASPS approach, highlighting its ability to work under very dynamic conditions.

7.0.2 Limitations

WASPS is not always better to be used when compared to existing models. The additional flexibility provided by WASPS also requires several parameters to be included. It is of course possible for many of these parameters to be nullified (e.g. assume all skill levels equal if population is homogeneous), but then that would require additional work in terms of domain implementation design. As WASPS is designed to be social, it would probably make more sense to use a different computational model rather than having to disable the social network aspect of WASPS, even though this too is possible. On the other hand, WASPS provides a relatively simple way to make use of features of both the genetic threshold and social inhibition models, as exhibited in 5. As we can see, WASPS provides a lot of flexibility, but is not necessarily the best option in all cases.

7.0.3 Future work

One idea that would be interesting to investigate is that not only can agents divide their resource among multiple tasks, but also that agents can divide multiple resources among multiple tasks. This seems rather intuitive to create as a variant of WASPS, but should still take a meaningful amount of work. Another idea is to expand on the work found in 5, allowing for the hybrid model to allow agents to divide work among multiple tasks. It would be interesting to see WASPS implemented in a large-scale economic simulation, as the emergence of specialization and its effects are important in that field. Moreover, I'd like to see WASPS investigated in terms of its use as a pareto optimization approach. The topic of task allocation is also an interesting problem that we believe WASPS can be applied to, especially in terms of how the self-organizing nature of it can work in the area of distributed task allocation. There are we are sure, many other uses and possible applications for WASPS which we cannot envision currently. In fact, the weight-allocated part of the model's name is now somewhat of a misnomer, as we have found uses for it whereby allocations are not weight allocated. It is my hope that WASPS will be improved upon and applied in many interesting ways, and that many of my assumptions will be overcome or modified. This work is not the definitive solution to the issue of the emergence of agent specialization. In fact, we believe that this work can be used as the foundation for addressing many more focused versions of this problem in many domains.

Bibliography

[1] J.E. Arnold and A. Munns. Independent or attached specialization: The organization of shell bead production in california. *Journal of Field Archaeology*, 21(4):473–489, 1994.

[2] A. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286: 509–512, 1999.

[3] A. Barabási and R. Albert. Scale-free networks. *Scientific American*, 288:60–69, 2003.

[4] B. Beaudreau. On the origins of large-scale specialization and exchange: A game-theoretical approach. In *The Canadian Economic Theory Conference*, Montreal, Canada, 2003.

[5] S.N. Beshers and J.H. Fewell. Models of division of labor in social insects. *Annu. Rev. Entomol.*, 46:413–440, 2001.

[6] J.T. Bonner. Dividing the labor in cells and societies. *Curr Sci*, 64:459–466, 1993.

[7] J.T. Bonner. Dividing the labor in cells and societies. *Current Science*, 64:459–466, 1993.

[8] J.T. Bonner. Perspective: The size-complexity rule. *Evolution*, 58:1883–1890, 2004.

[9] T. Bu and D. Towsley. On distinguishing between internet power law topology generators. In *INFOCOM*, 2002.

[10] L. Chai, J. Chen, Z. Han, Z. Di, and Y. Fan. Emergence of specialization from global optimizing evolution in a multi-agent system. In *International Conference on Computational Science*, number 4, pages 98–105, 2007.

[11] V. G. Childe. *Social Evolution.* Watts, London, 1951.

[12] D. Cockburn and Z. Kobti. The effect of social influence on agent specialization in small-world social networks. *IEEE Congress on Evolutionary Computing*, pages 3172–3175, 2009.

[13] D. Cockburn and Z. Kobti. Agent specialization in complex social swarms. *Studies in Computational Intelligence*, 248:77–89, 2009.

[14] D. Cockburn and Z. Kobti. Wasps: A weight-allocated social pressure system for the emergence of agent specialization. *European Conference on Aritificial Life*, pages 161–167, 2011.

[15] M. Dorigo and G. D. Caro. *The ant colony optimization meta-heuristic.*, chapter New Ideas in Optimization, pages 11–32. McGraw-Hill, 1999.

[16] R.K. Evans. *Early Craft Specialization: An Example for the Balkan Chalcolithic. In Social Archaeology: Beyond Subsistence and Dating.* Academic Press, New York, 1978.

[17] J.H. Fewell and R.E. Page. Colony-level selection effects on individual and colony foraging task performance in honeybees, apis mellifera l. *Behav Ecol Sociobiology*, 48:173–181, 2000.

[18] Goodwin B.C. Gordon, D.M. and L.E.H. Trainor. A parallel distributed model of the behavior of ant colonies. *Journal of Theoretical Biology*, 156:293–307, 1992.

[19] R. Gorelick, S.M. Bertram, P.R. Killeen, and J.H. Fewell. Normalized mutual entropy in biology: quantifying division of labor. *American Naturalist*, 164:678–682, 2004.

[20] J. Holland. *Hidden Order-how adaptation builds complexity.* Addison Wesley, MA, 1995.

[21] B. Hölldobler and E.O. Wilson. *The Ants*. Harvard University Press, Cambridge, Massachusetts, 1990.

[22] Z. Huang and G.E. Robinson. Honeybee colony integration: worker-worker interactions mediate hormonally regulated plasticity in division of labor. In *National Academy of Sciences*, volume 89, pages 11726–11729, 1992.

[23] R. Jeanson, J.H. Fewell, R. Gorelick, and S.M. Bertram. Emergence of increased division of labor as a function of group size. *Behavioral Ecology and Sociobiology*, 2007.

[24] C. David Johnson, Timothy A. Kohler, and Jason Cowan. Modeling historical ecology, thinking about contemporary systems. *American Anthropologist*, 107:96–107, 2005.

[25] G.E. Julian. *Genetic Variation and Task Organization in the Desert Leaf-Cutter Ant, Acromyrmex versicolor.* PhD thesis, Ariz. State Univ., Tempe, 1999.

[26] Z. Kobti and R.G. Reynolds. Modeling protein exchange across the social network in the village multi-agent simulation. In *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, volume 4, pages 3197–3203 Vol. 4, Oct. 2005. doi: 10.1109/ICSMC.2005.1571638.

[27] Z. Kobti, R.G. Reynolds, and T. Kohler. The effect of kinship cooperation learning strategy and culture on the resilience of social systems in the village multi-agent simulation. In *Evolutionary Computation, 2004. CEC2004. Congress on*, volume 2, pages 1743–1750 Vol.2, June 2004. doi: 10.1109/CEC.2004.1331106.

[28] Z. Kobti, R.G. Reynolds, and T.A. Kohler. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools 15*, 6: 963–978, 2006.

[29] T.A. Kohler. The final 400 years of pre-hispanic agricultural society in the mesa verde region. *Kiva*, 66:191–264, 2000.

[30] T.A. Kohler, C. D. Johnson, M. D. Varien, S. Ortman, R. Reynolds, Z. Kobti, J. Cowan, K. Kolm, S. Smith, and L. Yap. *The Model-Based Archaeology of Socionatural Systems*, chapter Settlement Ecodynamics in the Prehispanic Central Mesa Verde Region., pages 61–104. SAR Press, Santa Fe, New Mexico, 2007.

[31] T. Krink, B. Mayoh, and Z. Michalewicz. A patchwork model for evolutionary algorithms with structured and variable size populations. In *Genetic and Evolutionary Computation Conference*, 1999.

[32] J.B. Larsen. Specialization and division of labour in distributed autonomous agents. Master's thesis, University of Aarhus, 2001.

[33] A. M. Lavezzi. Complex dynamics in a simple model of economic specialization. Technical report, University of Pisa, 2003.

[34] A. M. Lavezzi. Smith, marshall and young on division of labour and economic growth. *European Journal of the History of Economic Thought*, 10:81–108, 2003.

[35] D. Merkle and M. Middendorf. Dynamic polyethism and competition for task in threshold reinforcement models of social insects. *Adapt. Behav.*, 12:251–262, 2004.

[36] S. Milgram. The small world problem. *Psychology Today*, pages 60–67, 1967.

[37] J.R. Zamora J. Murciano, A. Millán. Specialization in multi-agent systems through learning. *Biological Cybernetics*, 76(5):375–82, 1997.

[38] Dhruba Naug and Raghavendra Gadagkar. Flexible division of labor mediated by social interactions in an insect colony–a simulation model. *Journal of Theoretical Biology*, 197(1):123 - 133, 1999. ISSN 0022-5193. doi: DOI:10.1006/jtbi.1998.0862. URL `http://www.sciencedirect.com/science/article/B6WMD-45FSB7Y-55/2/013175aba5465adc912f3705236db64c`.

[39] M.J. North, N.T. Collier, and J.R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16 (1):1–25, 2006.

[40] S. O'Donnell. Rapd markers suggest genotypic effects on forager specialization in a eusocial wasp. *Behav. Ecol. Sociobiology*, 38:83–88, 1996.

[41] Scott G. Ortman. *GENES, LANGUAGE AND CULTURE IN TEWA ETHNOGENESIS, A.D. 1150-1400*. PhD thesis, Arizona State University, 2010.

[42] R.E.J Page, J. Erber, and M.K Fondrk. The effect of genotype on response thresholds to sucrose and foraging behavior of honey bees (apis mellifera l.). *J. Comp. Physiol. A*, 182:489–500, 1998.

[43] F. Ravary, E. Lecoutey, G. Kaminski, N. Châline, and P. Jaisson. Individual experience alone can generate lasting division of labor in ants. *Curr. Biol.*, 17:1308–1312, 2007.

[44] Robert G. Reynolds, Timothy A. Kohler, and Ziad Kobti. The effects of generalized reciprocal exchange on the resilience of social networks: An example from the prehispanic mesa verde region. *Computational & Mathematical Organization Theory*, 9:227–254, 2003. ISSN 1381-298X. URL `http://dx.doi.org/10.1023/B:CMOT.0000026583.03782.60`. 10.1023/B:CMOT.0000026583.03782.60.

[45] G.E. Robinson, R.E. Page, C. Strambi, and A. Strambi. Hormonal and genetic control of behavioral integration in honey bee colonies. *Science*, 246:109–112, 1989.

[46] Marshall Sahlins. *Stone Age Economics*. Aldine-Atherton, Chicago, 1972.

[47] C.E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 623–656, 1948.

[48] A. J. Spencer, I. D. Couzin, and N.R. Franks. The dynamics of specialization and generalization within biological populations. *Journal of Complex Systems*, 1(1):115–127, 1998.

[49] G. Theraulaz, E. Bonabeau, and J.L. Deneubourg. Response threshold reinforcements and division of labour in insect societies. In *Proc. R. Soc. Lond. B. Biol. Sci.*, volume 265, pages 327–332, 1998.

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[50] J.F.A Traniello and R.B. Rosengaus. Ecology, evolution and division of labour in social insects. *Animal Behaviour*, 53:209–213, 1997.

[51] C. R. Van West. Modeling prehistoric agricultural productivity in southwestern colorado: A gis approach. reports of investigations no. 67. Technical report, Department of Anthropology, Washington State University, Pullman, and, Crow Canyon Archaeological Center, Cortez, CO., 1994.

[52] Mark D. Varien, Scott G. Ortman, Timothy A. Kohler, Donna M. Glowacki, and C. David Johnson. Historical ecology in the mesa verde region: Results from the village ecodynamics project. *American Antiquity*, 72:273–300, 2007.

[53] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. In *R Soc Lond B*, number 273, pages 1815–1823, 2006.

[54] B. Winterhalder. Gifts given, gifts taken: The behavioral ecology of non-market intragroup exchange. *Journal of Archaeological Research*, 5:121–168, 1997.

[55] A. A. Young. Increasing returns and economic progress. *The Economic Journal*, 38: 527–542, 1928.

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Vita Auctoris

Denton Cockburn was born in 1982 in Kingston, Jamaica. He emigrated to Canada in 1993. He completed his Bachelor of Computer Science degree in 2003 at the University of Windsor. He would later complete his Bachelor of Science Honours degree with a Software Engineering focus in 2005 at the same university. Continuing his education at the University of Windsor, he would complete his Master of Science in Computer Science degree in 2007, when he finally applied to graduate, receiving his 3 degrees simultaneously. He defended for his Doctoral degree from the University of Windsor in December of 2011, graduating in June 2012.